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Power Demodulation of Local Field Potential Recordings

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Abstract— **Local field potentials (LFPs) are used to monitor the activity of large groups of neurons with macroelectrodes. Historically traditional linear statistical analysis techniques based on second order moments have been used to analyze these signals. We describe a new method based on power demodulation for estimating the instantaneous firing rate that is common to the neural activity of the most prominent neurons sensed by the electrodes. Correlated firing rates among neighboring neurons are common in many neurological structures and pathologies such as tremor. We validate our estimator with a Monte Carlo simulation based on a novel statistical model of LFPs. Our results show that the power demodulation approach can achieve a correlation of >0.80 with the common firing rate. This suggests that it may be possible to estimate the common intensity of a group neurons in recordings which are too noisy or contain too many neurons to apply spike detection or spike sorting algorithms.**

I. Introduction

Point process theory is often used to gain insight into extracellular neuronal recordings. The sequence of action potentials generated by a neuron can be thought of as a point process [1]. The actual morphology of each action potential is generally considered to contain little or no information and only the occurrence times are usually analyzed. The process intensity, or instantaneous firing rate, of a microelectrode recording (MER) is usually estimated by detecting the action potentials and then smoothing the resulting binary spike train [2]. An alternative method, called power demodulation, estimates the intensity essentially by squaring the signal and then smoothing [3]. This attains nearly the same degree of accuracy as spike train analysis and avoids the cumbersome, and sometimes difficult, task of detecting action potentials before further analysis.

In contrast, local field potentials (LFPs) contain action potentials from many neurons in a few cubic millimeters around the macroelectrode used to record them. LFPs primarily contain synchronous activity common to all of the neurons near the macroelectrode. Because of the size of these electrodes and number of neurons that they record from, it is impossible to perform spike detection or sorting. This difficulty leads many researchers apply spectral analysis to LFPs. Ideally, the LFPs should be used to estimate the synchronous activity of the neurons near the macroelectrode. More precisely, we would like to estimate the fluctuations in the firing rate that are common, or correlated, to all of the prominent neurons in the local area. We propose using power demodulation to estimate this common intensity.

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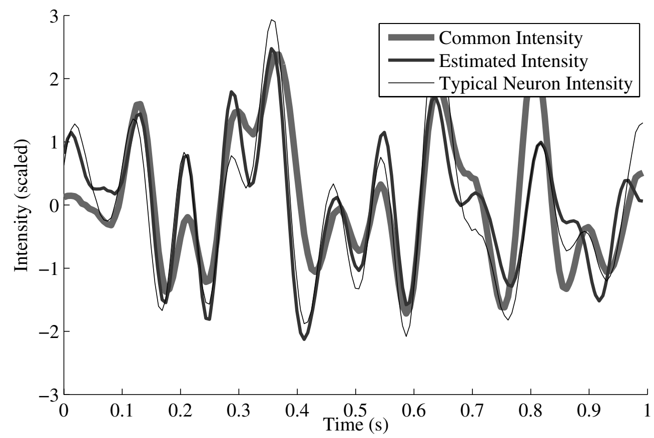

Fig. 2. The common intensity is the portion of the time varying intensity common to all neurons in the LFP. Estimated intensity is the power demodulation estimate of the common intensity. Typical neuron intensity is the time varying intensity of a single neuron.

A LFP can be modeled as a weighted sum of the extracellular potentials of the neurons within a few millimeters of the electrode. Thus the LFP can viewed as microelectrode recording with many neurons. We use this to extend the statistical model developed for single-neuron MERs in [3] for modeling the properties of LFPs.

II. Methodology

A. Statistical Model

Fig. 1 shows a block diagram of the method used to create synthetic LFP signals. A bandlimited signal, $v_0(n)$, is created by bandpass filtering a white noise sequence. The goal of the intensity estimator is to estimate this signal. It represents the variation in process intensity common to all of the prominent neurons recorded in the LFP. The intensity of the kth neuron, $m_k(n)$, is created by taking a weighted average of the common intensity $v_0(n)$ and the intensity that is specific to that neuron, $v_k(n)$. If $v_0(n)$ and $v_k(n)$ have equal variance, the time-varying intensity of the kth neuron is given by,

$$m_k(n) = v_0(n)\sqrt{\rho} + v_k(n)\sqrt{1-\rho} \qquad (1)$$

where ρ is the correlation between $m_k(n)$ and $v_0(n)$. Fig. 2 shows a typical realization of the common intensity, v_0, the intensity of a single neuron, $m_k(n)$, and the estimated common intensity, $\hat{v}_0(n)$.

The time varying neuron intensity, $m(n)$, is used as a modulating signal, which is scaled and added to the average

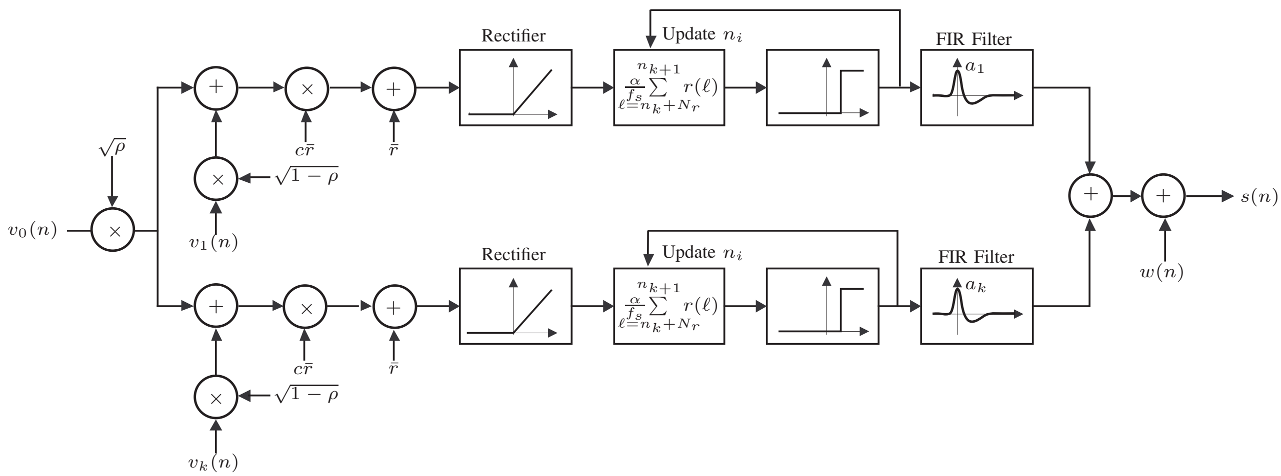

Fig. 1. Block diagram of the method used to generate synthetic recordings.

firing rate, $\bar{r}$, to produce the total process intensity, $r_k(n)$.

$$r_k(n) = \left(\bar{r}\left[1 + c\frac{m_k(n)}{\sigma_m}\right]\right)_+ \tag{2}$$

c is the coefficient of variation and controls how variable the intensity will be about its mean. The standard deviation of $m_k(n)$ is controlled by σ_m and $(\cdot)_+$ denotes the half wave rectifier operation. The spike indices for the point process are calculated by solving the following equation for the smallest n_{i+1} such that,

$$\frac{\alpha}{f_s}\sum_{l=n_i+N_r}^{n_{i+1}} r(l) \geq \mathcal{I}_k \tag{3}$$

where $\mathcal{I}_i$ is a gamma random variable with shape parameter a and scale parameter $1/a$, N_r is the repolarization time in samples, and α is a scaling factor to ensure the mean intensity is equal to the average firing rate $\bar{r}$. This can be calculated by

$$\alpha = \frac{1}{1 - T_r\bar{r}} \tag{4}$$

where T_r is the repolarization time T_r. The starting index of the sum N_r is then given by

$$N_r = f_s T_r \tag{5}$$

where f_s is the sampling rate.

This model can be used to create point processes of coupled neurons with a known common intensity. Fig. 3 shows an example spike train and its intensity created with this model.

The spike train that results is filtered with an FIR filter to produce an action potential morphology at each spike. The impulse response of this filter is shown in Fig. 4 and given by,

$$h(-t) = \frac{1}{s_d}\mathrm{e}^{-(\frac{t}{s_d})^2} - \frac{1}{s_r}\mathrm{e}^{-(\frac{(t-t_r)}{s_r})^2} \tag{6}$$

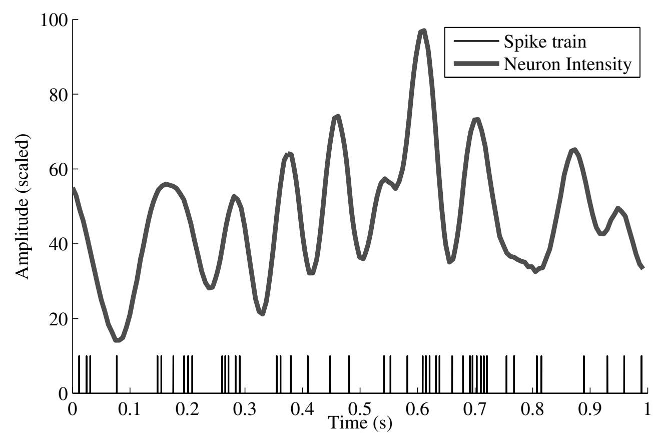

Fig. 3. Spike train and process intensity. The average firing rate is $\bar{r}$=50 Hz.

where s_d determines the width of the depolarization pulse, t_r determines the repolarization delay, and s_r determines the repolarization width.

This single neuron signal is then scaled by the inverse of it's distance. The distance from the electrode is given by

$$d = \sqrt{x^2 + y^2 + z^2} \tag{7}$$

where x, y, and z are random variables representing the position of the cell in relation to the electrode. We assume that they are normally distributed, making d^2 distributed as χ^2 with three degrees of freedom. This process is repeated for each simulated neuron. The resulting signal is given by

$$s(n) = w_s(n) + \sum_{k=1}^{N} s_k(n) \tag{8}$$

where $s_k(n)$ is the scaled individual neuron signal and $w_s(n)$ is white noise scaled to have variance equal to the variance of the sum of individual neurons divided by the SNR. Fig. 5 shows an example synthetic LFP signal.

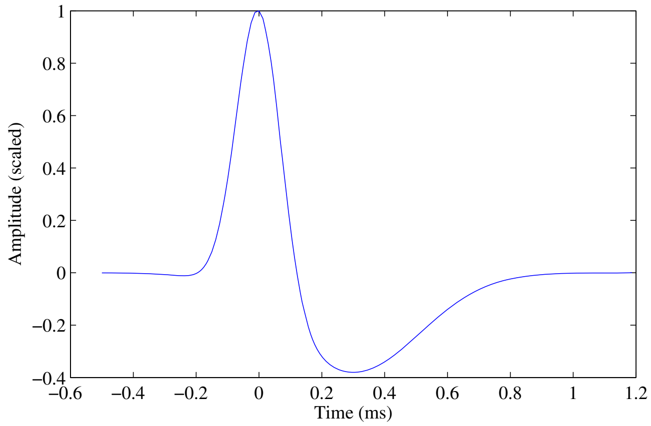

Fig. 4. Action potential morphology.

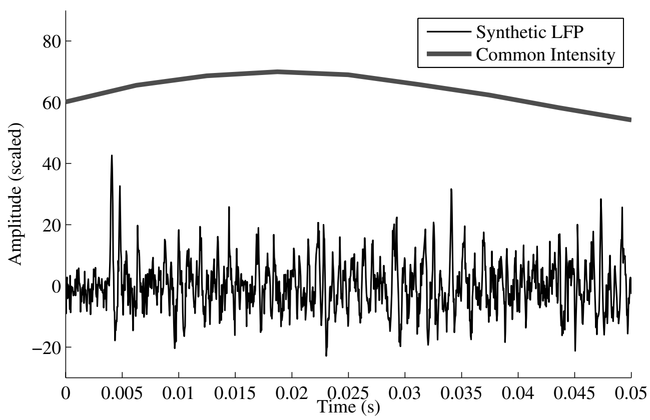

Fig. 5. Synthetic LFP signal and its common intensity.

B. Power Demodulation Intensity Estimation

The power demodulation approach to intensity estimation is a three step process. The first stage is a bandpass filter with a cutoff frequency of $f_s/4$. For $p = 2$ this prevents the second stage, a nonlinear-rectifier $|s(n)|^p$, from causing aliasing since squaring a signal doubles its effective bandwidth. The third stage is a second bandpass filter which simply attenuates the estimation error that is outside of the bandwidth of the signal being estimated, $v_0(n)$. Since $s(n)$ is typically sampled at high frequencies ($f_s > 10\,\text{kHz}$) and the bandwidth of the time-varying intensity is generally assumed to be much less than the firing rate of the neuron, this filter attenuates a large fraction of the incoming signal power. In most applications this second filter would be specified to have a non-negative impulse response and its purpose would be to simply smooth (i.e., lowpass filter) the input signal [2].

The key idea inspires this type of demodulation is that the intensity of the point process is approximately equal to the instantaneous power of the microelectrode recordings. This can be understood by expressing the observed signals as

$$s(n) = w_s(n) + b(n) * h(n), \tag{9}$$

$$= w_s(n) + \sum_{i=1}^{N_s} h(n - n_i), \tag{10}$$

where $b(n)$ is the binary spike train given by

$$b(n) = \sum_{i=1}^{N_s} \delta(n - n_i), \tag{11}$$

N_s is the number of spikes in the recording, n_i is the sample index of the ith spike occurrence, and $\delta(n)$ is the unit impulse, also known as the Kronecker delta function. When a spike occurs, the instantaneous signal power, $p(n) = |s(n)|^2$, increases because both $w_s(n)$ and $h(n - n_i)$ contribute to the signal power. When no spike is present, the expected signal power is equal to that of the noise. Thus, the instantaneous power signal contains a low-frequency component that fluctuates with the intensity. This is component can be estimated with a lowpass filter in exactly the same manner that is applied to spike trains [2].

C. Performance Metric

The goal of the demodulator is to estimate the portion of the time varying intensity $v_0(n)$ common to all of the neurons. The estimate is not expected to have the same scale as $v_0(n)$ and is not expected to estimate the mean intensity, $\bar{r}$. The coefficient of determination, ρ^2, is invariant to linear signal transformations and can be interpreted as an estimate of the explained variation of $v_0(n)$. If the estimated intensity is scaled to have zero mean and unit variance like $v_0(n)$, ρ^2 can be estimated as

$$\rho^2 = [\frac{1}{N} \sum_{n=1}^{N} v_0(n) \hat{v}_0(n)]^2 \tag{12}$$

This measure is bounded, $0 \leq \rho^2 \leq 1$. If $\rho = 0$, the signals are fully uncorrelated. If $\rho = 1$, the signals are perfectly correlated.

III. Results and Discussion

Two parameter sweeps were performed with the model presented in this paper. For each parameter value the average of 50 simulations is shown with the shaded area representing the interquartile range. Table I lists the simulation parameter values.

The amount of correlation between individual neuron intensities and the common intensity is shown in Fig. 6. The correlation between a neuron's intensity and the common intensity, ρ, is varied directly as a model parameter in Eq. 1. This figure shows that as the individual neuron intensities become more correlated to the common intensity the common intensity becomes easier to estimate.

Fig. 7 shows how the number of neurons affects the performance. Initially, as neurons are added they have a large impact on the performance, but it soon reaches a point of diminishing returns where adding additional neurons has little effect on performance.

TABLE I

SUMMARY OF USER-SPECIFIED PARAMETERS USED FOR SYNTHETIC LFP GENERATION AND INTENSITY ESTIMATION.

Name	Symbol	Value
Sample Rate	f_s	25 kHz
Modulating Signal Bandwidth		0-15 Hz
Number of Neurons		50
Correlation	ρ	0.7
Signal Duration	T	10 s
Refractory Period	T_r	3 ms
Mean Intensity	$\bar{r}$	50 Hz
Coefficient of Variation	c	0.3
Signal-To-Noise Ratio	SNR	5
Shape Parameter	a	1
Rectifier Power	p	2
Filter Passband Attenuation		$< 1.2\,\%$
Filter Stopband Attenuation		$> 99.0\,\%$
Depolarization Width	s_d	0.1 ms
Repolarization Width	s_r	0.3 ms
Repolarization Delay	t_r	0.3 ms

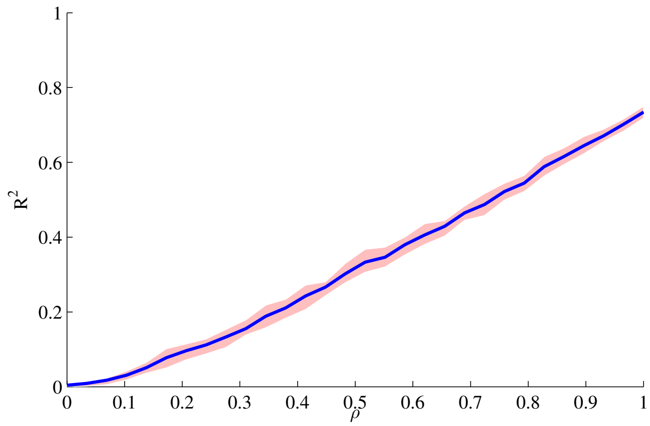

Fig. 6. ρ is the correlation between the neuron's intensity and the common intensity.

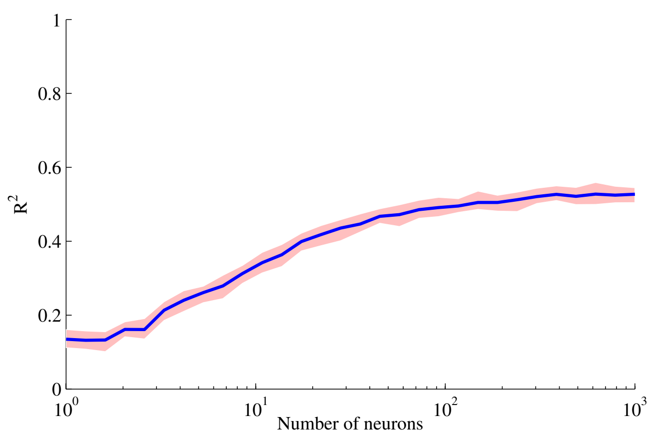

Fig. 7. Performance of the estimator as the number of neurons is varied.

IV. CONCLUSION

This paper described a statistical model for LFP recordings based on a weighted sum of point processes for each neuron. A method for estimating the process intensity common to a local area was proposed. The results suggest that the time varying intensity of a group of neurons can be estimated accurately using power demodulation. This shows that simple nonlinear processing may permit the common intensity of a large group of neurons to be estimated without the necessity of spike detection or spike sorting algorithms, which cannot be applied to LFPs.

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