Neural Engineering

Neural signal processing:

1. Spike sorting:

Spikes from closer neurons produce larger amplitude deflections in the recorded signal. The goal of signal processing methods for such an input signal is to reliably isolate and extract the spikes being emitted by a single neuron per recording electrode. This procedure is usually called spike sorting. The simplest spike sorting method is to classify spikes according to their peak amplitude. Sometimes, the peak amplitudes may be the same for different neurons, making the method not feasible. A better approach is the window discriminator method in which the experimenter visually examines the data and places windows on aligned recordings of spikes of the same shape. The recent trend has been toward clustering spikes automatically into groups based on shape, where each group corresponds to spikes from one neuron. The shape of a spike is characterized by features extracted using wavelets or dimensionality reduction techniques.

2. Temporal and spatial feature extraction:

Key temporal and spatial features can represent and help us understand the neural activity from the underlying oscillations. The neural signals recorded from the brain are typically mixture potentials resulting from network activity of a large population of neurons around the local neighborhood. Thus, applying appropriate feature extraction methods can isolate and extract significant features in both temporal and spatial domains.

Spatial filtering:

For some methods that record brain signals using multi-electrodes, the signals are recorded from multiple regions of the brain. With the large variance of global noise, the local signals appear diminished. Therefore, spatial filtering or re-referencing methods are applied to enhance the local activity and filter out the common noise. For individual electrodes, the averaged activity from surrounded electrodes (Laplacian filtering) or from global electrodes (common averaged referencing) is subtracted. Spatial filtering methods can also be used to estimate the variance of the neural data.

Temporal analysis:

The quality of the recorded brain signals primarily depends on recording techniques. However, the recorded time-series signals contain lots of noise that can be filtered using time-domain filtering methods. Numerous filtering techniques like moving average smoothing, exponential smoothing, etc. are used to preprocess raw signals in the time domain.

In addition to filtering, temporal analysis can also be used to extract significant features that represent behavior. These significant features can be extracted out from a series of time signals using computational models. Some neural signals tend to be correlated over time, and thus, the following time samples are possible to be predicted based on the previous samples using autoregressive models (for stationary signals) or adaptive autoregressive models (for nonstationary signals). Such methods depend on the model built up from the characteristic internal relationships between the previous signal samples and the subsequent samples. The coefficients of the model can be considered as neural features for the subsequent pattern recognition or classification procedure utilized for real-time decoding or estimation.

Frequency analysis:

While temporal analysis methods are useful, there are some signals for which these methods may not result in extracting meaningful features. For example, noninvasive methods such as EEG are based on signals that reflect the activity of several thousands of neurons. Poor spatial and temporal resolution challenges the feature extraction in the time domain. The recorded signal thus can capture only the correlated activities of large populations of neurons, such as oscillatory activity.

The intrinsic property of the brain signals is neuronal oscillations. Theoretically, these oscillations can be decomposed with a set of basis functions, such as sinusoid functions using Fourier transform (FT) for periodic signals. For each cycle, the amplitude, the period, and the waveform symmetry are measured and oscillatory bursts are algorithmically identified, allowing us to investigate the variability of oscillatory features within and between bursts. Usually, for neural signals, short-time Fourier transform (STFT) provides better results by performing FT with sliding short-time windows. For the nonperiodic signals, the wavelet transform is applied for signal decomposition. A variety of scaled and finite-length waveforms can be selected according to the shape of the raw neural signals. The wavelet coefficients sometimes contain unique information which can be considered as neural features. Additionally, the power spectrum of neural signals usually reflects lots is important information, such as power spectral density (PSD).

Time-frequency analysis:

By combining the advantages of temporal and frequency analyses, the researchers realized the power of time-frequency analysis. As an example, using decomposition techniques, a signal can be decomposed into intrinsic mode functions (IMF) and instantaneous frequencies over time can be obtained by applying methods such as Hilbert spectral analysis. The most significant advantage of this technique is that the nonlinear, nonstationary recorded neural signals can be transformed into linear and stationary components. These components are usually physically meaningful since the special features are localized in their instantaneous frequencies and represent meaningful behavioral information in the time-frequency domain. Time-frequency analysis is extensively implemented in neural signal processing since the individual analysis in the time or frequency domain comes with respective disadvantages, and time-frequency analysis trades off time and frequency resolution to get the best representation of the signals. Other techniques such as spectrogram and STFT are most performed by segmenting a signal into short periods and estimating the spectrum over sliding windows.

Dimensionality reduction:

A critical procedure in neural signal processing is to reduce the high dimensionality of the recorded neural data. These data could be brain images, multi-electrode signals, network potentials, or high-dimensional neural features. Several algorithms can be applied linearly or nonlinearly to preserve the most useful components and remove redundancies. Principal component analysis (PCA) is to find the direction of maximum variance and thereby build the principal components (weighted linear combinations) based on the observed variance. Linear discriminant analysis (LDA) performs similar to PCA but tends to minimize the variance within a group of neural data and maximize the distance between groups of neural data. Thus, PCA is described as an unsupervised algorithm implemented for feature extraction, and LDA is described as a supervised algorithm that uses training based on labels for groups of data. Other methods that are used most often are CCA and ICA. Canonical correlation analysis (CCA) is yet another method for exploring the relationships between two multivariate sets of variables allowing us to summarize the relationships into a lesser number of variables while preserving the essential features of the relationships. Independent component analysis (ICA) is a blind source separation method rather than a dimensionality reduction method. Neural signals consist of recordings of potentials that are presumably generated by mixing some underlying components of brain activity. ICA can theoretically isolate these underlying components of brain activity by computing independent components. Additionally, ICA can also be used as a filtering method to remove signal artifacts generated by eye blinks or other artifacts in EEG signals.

Machine learning algorithms:

Machine learning or deep learning algorithms have become increasingly popular and are being implemented in many fields. They can be broadly divided into unsupervised learning and supervised learning. Unsupervised learning methods aim to extract hidden structures within the neural data, commonly used for feature extraction, pattern recognition, clustering, and dimensionality reduction. Supervising learning methods train the neural data using underlying functions to map to a given output and automatically discover the relationships between input data and output labels. The most common applications of supervised learning are classification and regression. Quantitative models of machine learning algorithms provide incredibly powerful implementations in neuroscience. Some traditional methods such as LDA, PCA, and support vector machine (SVM) are also regarded as machine learning algorithms. Other algorithms (neural networks, autoencoders, and logistic regression) train batches of input data using basis transformation function to match the output adaptively.

Applications of neural signal processing:

Neuroprostheses, neurostimulators, or human-machine interfaces are devices that record from or stimulate the brain to help individuals with neurological disorders, restore their lost function, and thereby improve their quality of life. Neural signal processing methodologies are used extensively in all these applications.

- ## Neurostimulators:

Neurostimulators that have demonstrated decades of success are cochlear implants that are designed for those who have dysfunctional conduction of sound waves from the eardrum to the cochlea. These implants can also help elderly individuals who have age-related hearing loss. There is an external speech processor to capture and convert the sound from the surrounded environment to digital signals. The internal implants turn the digital signals into electrical signals to stimulate the hearing nerve by the electrodes inside the cochlea. Once the brain receives the signals, one can hear and interpret the sound.

Another successful neurostimulator is the deep brain stimulator (DBS) system used for individuals with Parkinson's disease. The DBS has been available as a reliable treatment for decades for individuals with Parkinson's disease. The implanted impulse generator placed under the collarbone provides continuous electrical impulses by giving a certain frequency of stimulation to the subthalamic nucleus and makes it possible to minimize the uncontrolled tremors. During the DBS surgery, electrodes are inserted into a targeted area of the brain, and the whole procedure is monitored and recorded using MRI. After the treatment, symptomatic improvement was durable for at least 10 years.

- ## Neuroprostheses or human-machine interfaces (HMIs):

Stroke, spinal cord injury, and traumatic brain injury may lead to long-term disability, and an increased number of individuals are suffering from severe motor impairments, resulting in loss of independence in their daily life. Recovery of motor function is crucial in order to perform activities of daily living. Human-machine interfaces (HMIs) can enable dexterous control of exoskeletons that could be used as a rehabilitative device or an assistive device to restore lost motor functions poststroke or spinal cord lesions , thus promoting long-lasting improvements in motor function of individuals with movement disorders.

Additionally, significant applications in neural engineering are HMI-based systems to restore or compensate the lost limb functions for individuals with amputation or paralysis. Cortical control of prosthetics has been studied both in animals and humans. Movement-related cortical potentials used to assess cortical activation patterns provide interesting information, as they are associated with the planning and execution of voluntary movements. Recently, HMI-based research has stressed on the development of algorithms for movement decoding using noninvasive neural recordings. In order to understand neural intent before or during the movement, it is necessary to extract the characteristics accurately using efficient algorithms. The adaptability and reliability over the long-term are current challenges that are being addressed using advanced and adaptive signal processing methodologies. Months to years of training are essential to operate prosthetic or exoskeleton skillfully. This training time can possibly be reduced by increasing the burden on machine learning algorithms that are currently being addressed by advanced signal processing methods.

- ## Neurological disorders:

Epilepsy is a common neurological disorder characterized by an enduring predisposition to generate epileptic seizures. These seizures may cause disturbances in movement, loss of control of bowel or bladder function, loss of consciousness, or other disturbances in cognitive functions. Currently, the signal processing algorithms can detect ongoing seizures and provide clinicians with detailed information such as localization of seizure foci useful for the treatment of epilepsy. The ability to detect seizures rapidly and accurately could promote therapies aimed at rapid treatment of seizures.

Skilled neurophysiologists visually examine the neural signals and detect epilepsy. Apart from the single-channel signals, other contextual information such as spatial and temporal data are vital to neurophysiologists for recognizing spikes. Currently, the epileptic seizures can be detected and predicted from EEG or ECoG signals by extracting the hidden features using machine learning algorithms.