Transformation in Neural Signal Processing

Junjie Gao, School of Electronic Information and Electrical Engineering, Shanghai Jiao Tong University, Shanghai, China
e-mail: ruizesun00@sjtu.edu.cn

***Abstract*—Neuroscientists are always seeking efficient solutions for discovering the mystery of brain. The effective development of brain related tools is the key point of research in neuroscience and neurotechnology. Nowadays, the physical development of high-density and high-resolution neural interfaces has been made possible. This is where the critical bottleneck in receiving the expected functionality from such devices shifts to transferring, processing, and subsequently analyzing the massive neurophysiological extra-cellular data recorded. To respond to this inevitable concern, a spectrum of neuronal signal processing techniques have been proposed to extract task-related informative content of the signals conveying neuronal activities, and eliminate the irrelevant contents.Such techniques provide powerful tools for a wide range of neuroscience research, from low-level perception to high-level cognition. Data transformations are among the most efficient processing techniques that serve this purpose by properly changing the data representation. Mapping the data from its original domain (i.e., the time-space domain) to a new representational domain, data transformations change the viewing angle of observing the informative content of the data. This paper reviews the employment of data transformations in order to process neuronal signals and their three key applications, including spike detection, spike sorting, and data compression.**

***Index Terms*—Data Transformation, Neural Signal Processing, Spike Sorting.**

I. Introduction

INFORMATION in the brain flows through a network of around 80-100 billion massively-interconnected neurons [1]. To utilize the information in the brain, the scientists have to monitor brain activities and connections.Moreover, researchers investigate brain functions as well as their correspondence with sensory information (e.g., for brain mapping) through the modulation of brain activities. Therefore, the techniques and devices developed for brain function monitoring and modulation play a critical role in the progress of neuroscientific research.

Advanced behavioral and functional brain research typically requires the acquisition of voluminous neural activities from the brain. Nowadays, intra-cortical electrode arrays with more than one thousand recording sites have been reported [2]. Technical advancements such as the maturity of microelectromechanical systems (MEMS) fabrication technology have paved the way towards developing of high-density, high-performance tools to interface with the brain. As a result of increasing data volume, computational and hardware implement costs in terms of data storage capacity, data transfer rate, physical size, and electrical power increase. Therefore, analysis of the data acquired by high-density neural recording probes appears to be a big challenge for advanced neuroscience research [3]. To overcome this challenge, a large amount of techniques have been used to eliminate unnecessary data while maintaining the informative components of recorded signals. In some sense, the main processing techniques used for this purpose can be divided into (a) *spike detection*, (b) *spike sorting*, (c) *data compression*. Spike detection could separate neural spiking activities from the background noise or Local Field Potentials(LFPs) in the recorded signals. Spike sorting could isolate different classes of neural activities based on their origin, ie., *units*. Data compression could reduce the amount of data while preserving the informative components. Generally, the techniques mentioned above are widely used in neural data acquisition and neural signal decoding.

To exploit the information of data, a common method is to transform the representation space of data. In this paper, the data transformations in neural signal processing and their main application will be reviewed. First, the prior knowledge of neural signals and their processing will be discussed. Then, the commonly used transformations in neural signal processing are introduced. Finally, the applications of the transformations are provided.

II. Neural Signal and Processing

In the 18th century, Galvani discovered that cells in the nervous system of frogs generate electric pulses [1]. In 1952, using intra-cellular recording and chemical manipulation, Alan Hodgkin and Andrew Huxley introduced a mathematical model for neuronal signaling in the squid giant axon [3]. The Hodgkin-Huxley model well described the electrochemical mechanism of initiation and propagation of neuronal spikes (action potentials). In 1959, David Hunter Hubel and Torsten Wiesel used the single-channel extra-cellular recording to study the functional organization of the cat's primary visual cortex [4]. Their discoveries paved the way for analyzing information in neuronal networks and brain mechanisms for perception.

In 1964, Gerstein and Clark began using computer algorithms to analyze and process neuronal data [5]. Thereafter, employing computationally-powerful benchtop systems, various mathematical tools were used for the processing of neuronal signals. Then, through the fabrication of silicon-

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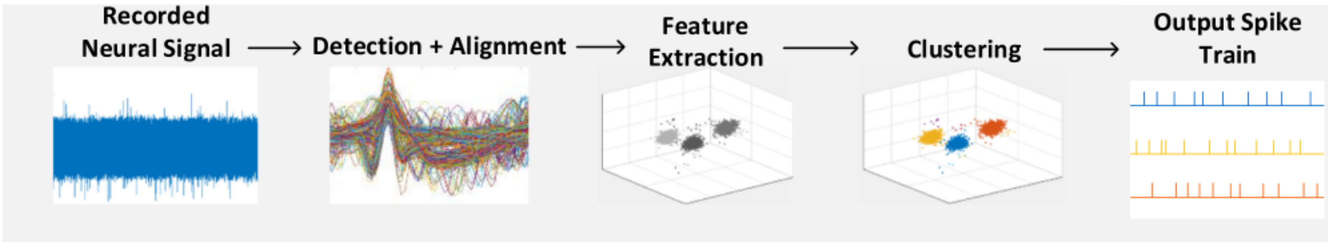

Fig. 1. The spike sorting pipeline, recorded neural signal is filter and digitized first, after spike detection and alignment, the spikes will be passed to feature extraction. The different spikes will be separated in feature domain by clustering.

based microelectrode arrays (MEAs) in the late 20th century, the recording capacity of such systems increased considerably. The prominent instances for such MEAs are Michigan and Utah electrode arrays. The former was introduced by Kensall D Wise, James B Angell, and Arnold Starr in 1970 [6], and the latter was reported by Patrick K. Campbell, Richard A. Normann, et al. in 1991 [7]. In 2005, Roy H. Olsson and Kensall D. Wise introduced an implantable neural recording microsystem equipped with on-chip digital signal processing [8]. Subsequently, in 2007, Karim G. Oweiss, Andrew J Mason, et al. reported on a hardware-efficient signal processing technique based on wavelet transform [9]. Next, in 2009, Amir M. Sodagar, Khalil Najafi, and Kensall D. Wise pre- sented a fully-implantable integrated microsystem containing recording front-end, on-chip processing, and wireless backend [10].

Since the introduction of micro-fabricated MEAs, the recording capacity of neural interfacing devices (i.e., channel count) has been continuously increased [3]. Owing to the maturity of the micro-fabrication technology, many ultra-high-density electrode arrays have been reported recently [2]. Fast growth in the number of recording channels helps scientists capture voluminous data from the brain, necessitating sophisticated signal processing tools to handle the recorded data. To respond to this inevitable need, an on-chip data processing framework and hardware on as high as 512-channels has been recently reported by MohammadAli Shaeri and Amir M. Sodagar [11].

Thanks to previous works in the neural signal acquisition, it is possible for researchers nowadays to further discover the information in these signals. Then, neural signal and processing sequence will be discussed seperately.

A. Neural Signal

Neuroscientists use a wide variety of signals to study brain activities. These signals are commonly acquired via different recording method, including magnetic (eg., MRI), optical (eg., Calcium imaging), and electrical (eg., EEG). This review will focus on the electrical signals. The electrical signals include two categories: supra-cortical signals and intra-cortical signals. Supra-cortical signals (EEG and ECoG) convey macro-scale information from brain activities [12]. Intra-cortical signals contain LFP, conveying more localized yet macro-scale infromation, and neural spike (Action Potentials, APs)[13].

In this paper, we keep our focus on analyzing the intra-cortical neural signals. Specifically, we review the techniques for processing *Spikes* . The firing rate of spike represents average neural activities of a certain neuron, known as *single-unit activity* (SUA). To form spike train for individual neurons, the spike sorting is necessary. Without spike sorting, the signal is known as multi-unit activity (MUA) which is a mixture of SUAs [14].

B. Neural Signal Processing

To extract the informative components of a neural signal need corresponding signal processing, which includes three stages: *pre-processing, core-processing,* and *post-processing.* Specifically, raw brain signals acquired from the brain using an electrode array are first preconditioned in the analog domain (amplified and filtered) and then digitized [10]. Consequently, the prepared neural signals could be further processed in the digital domain. Through core-processing, digital signal processing techniques are applied to the neuronal signals in order to extract their task-relevant informative contents. Finally, at the post-processing step, the digital data conveying the informative content of the recorded signals is structured (i.e., encoded, formatted, and/or framed) for transmission, storage, visualization, or further analysis of data in a host device.

In spike sorting pipeline, the core signal processing is composed of *Detection, Alignment, Feature Extraction*, and *Clustering,* as shown in Fig 1. While the recorded neural signal is filtered and digitized, one could use spike detection to extract the spikes,ie.,SUAs, from the background noise components. Then the detected spikes will be aligned to prepare for consequent processing. Alignment is necessary because only in this way the feature extraction processing could extract the features precisely. In feature extraction, the features of aligned spikes are extracted, which could reduce the dimension of signal. Finally, the feature will be used to cluster to classify different class of spikes, constructing the spike trains.

III. Transformation in Neural Signal Processing

To finish signal processing mentioned above, a wide variety of data transformations have been used. In this chapter, some common transformation will be discussed, which could be categorized into time-domain analysis, frequency domain analysis, time-frequency analysis and other transformations.

A. Time-domain analysis

The derivative transform is a simple transform in the time-domain. The first-order derivative of a signal measures its slope over time. Higher-order derivatives provide information on how the lower-order variations of the signal change in time. In the discrete-time, the derivative operation is realized by taking the difference between two consecutive samples. In general, the n^{th} derivative of the discrete-time signal $X[k]$ is defined as:

$$X^{(n)}[k] = X^{(n-1)}[k] - X^{(n-1)}[k-1], n \in 1, 2, ... \tag{1}$$

where $X^{(n)}[.]$ is the n^{th} discrete derivative of the signal, k denotes the time index. Derivative transforms of different orders have been suggested for the separation of spikes from noise [15], spike isolation [16], and data compression [17].

One of the main characteristics of neuronal spiking activities is their relatively large and fast amplitude variations.The Teager energy operator (TEO), also known as the Non-linear energy operator (NEO), is used to discriminate spiking activities from the background noise in a neuronal signal. According to [18], the TEO transform is defined as:

$$T[k] = X[k]^2 - X[k+1]X[k-1] \tag{2}$$

which highlights rapid signal changes (e.g., neuronal spikes) and attenuates slow-transition contents (e.g., low-frequency noise).However, this transform is not capable of distinguishing between spikes and high-frequency noise. This degrades the efficacy of the TEO transform for low signal-to-noise ratios. Addressing this shortcoming, the multi-resolution TEO (MTEO) provides tunable temporal resolution[19]:

$$T_m[k] = X[k]^2 - X[k-m]X[k+m] \tag{3}$$

B. Frequency-domain analysis

In digital signal processing, discrete Fourier transform (DFT) is a classic method for frequency analysis. The DFT converts a signal to a series of complex sinusoids, representing the signal content using orthogonal frequency components [20].The DFT, therefore, transforms the finite-length, discrete-time signal from the original domain (i.e., the time domain) to the discrete frequency domain. The discrete Fourier transform of a finite-length, time-domain signal, $X[k]$, is formulated as:

$$F[f] = \sum_{k=0}^{K-1} X[k] \cdot e^{-j\Omega_0 kf}, \Omega_0 = 2\pi/K \tag{4}$$

where F[f] denotes the DFT coefficients of the signal, representing the signal content at the frequency f, and K is the total number of signal samples in the time domain.

When a signal is of even symmetry, the summation in equation (4) is reduced to a sum of cosine terms, known as the discrete cosine transform (DCT) [20]. To express the frequency content of a time-domain signal using the DCT, first, a mirrored version of the signal is concatenated to the original signal in order to make it even symmetric. Then, the DFT of the resulting signal is calculated. Alternatively, a neuronal signal can be decomposed into a set of two components: the exponential component and the polynomial component. This is done by the harmonic analysis performed using the Hilbert transform, the result of which is separate representations for the neuronal spikes and the noise content of the signal using the exponential and polynomial components, respectively [21].

C. Time-frequency analysis

There also exists a spectrum of transforms for time-frequency analysis of signals, examples of which are the short-time Fourier transform (STFT) and the wavelet transform [22]. The STFT is taken by calculating the Fourier transform over a fixed-width sliding time window. On the one hand, the transformed signal maintains the time-frequency content of the input signal. On the other hand, due to the uncertainty principle for time and frequency [22], the resolution of the transformed signal content in both time and frequency domains at once is strictly limited. In other words, the uncertainty principle implies that the wider the window is in the time domain, the more precise the representation will be in the frequency domain, and vice versa.

The wavelet transform expands input vectors, signals, or functions into primitive short waves, called ‘wavelets’, which can all be expressed using a single mother wavelet function. The expansion using the wavelet transform is performed by time shifts (translations) and time scaling of the mother wavelet function. Although the Fourier transform does not indicate which frequency component exists at what time, the wavelet transform decomposes localized content of the frequency components across time. Instead of frequency analysis, as it was the case for DFT and STFT, the wavelet transform essentially analyzes the signal based on the ‘scales’ that determine dilations or contractions of the wavelet function. This analysis indeed measures average signal oscillations in multiple scales.

The basis function used for the wavelet transform can be chosen from a wide variety of certain functions. The wavelet transformation of a signal is performed by convolving the signal with the mother wavelet function. The type of wavelet transform is defined by its wavelet function, which measures a different set of components. The proper choice of the wavelet function is sometimes made according to what we expect from the transform. Fig. 2 presents some of the wavelet functions that have been previously used for the processing of neural spikes [9].

D. Other transformations

The Principle Component Analysis (PCA) method seeks the uncorrelated orthogonal dimensions that describe the data with the maximum possible variance. Known as the principal components, these dimensions are used to linearly compose a transform for the input data. Another technique commonly used to form a data-fitted transform is the Independent Component Analysis (ICA). The ICA technique suggests a linear composition of statistically-independent source signals, which makes ICA approach a proper choice for blind source separation.

Unlike the above decomposition techniques, a different approach works based on a dictionary of fundamental elements

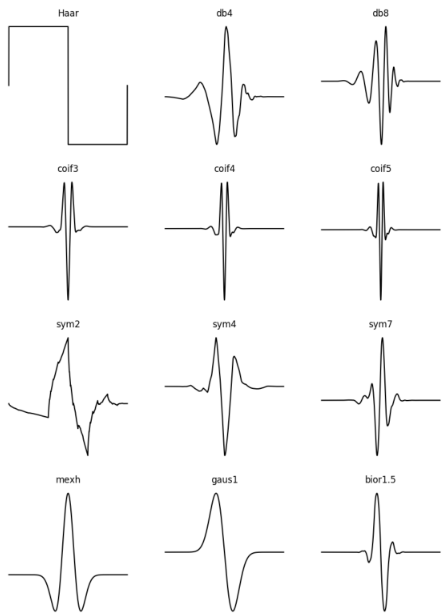

Fig. 2. The mother wavelet families used for neural signal processing.

that are not necessarily independent nor orthogonal. These dictionary elements are used to compose a linear and sparse representation for the input signal. A variety of dictionary learning algorithms are suggested to find the best primitive atoms that fit the input data.

Based upon the graph theory, graph-Laplacian features (GLF) [23] is a linear transformation, which looks for both maximum variance and minimum graph Laplacian at the same time. Locality Preserving Projections (LPP) is another linear feature mapping algorithm that constructs a graph according to the neighborhood information of data-points yet preserving the intrinsic geometry of the data. Then, a representational space is formed based upon the acquired adjacency graph [24].

Linear Discriminant Analysis (LDA) is a supervised linear transformation that uses the Fisher criterion to find orthogonal discriminant dimensions by maximizing the overall separation of class distributions [25]. Salient feature selection (SFS) picks the most salient features according to both the overall between-class distance and the associated homogeneity. Subsequently, the SFS technique forms a space of uncorrelated salient features, discriminating a spike class from other classes in a supervised manner.

In case the data is scattered with a complicated pattern, non-linear transforms are potential solutions to retain the general characteristics of complicated manifolds. Manifold learning methods such as non-linear isometric feature mapping (IsoMap) [26], Laplacian eigenmaps (LE) [27], and the t-Distributed Stochastic Neighbor Embedding (t-SNE) method [28] were previously suggested approximating a low-dimensional manifold based on the intrinsic geometry of the data. Moreover, there are some artificial neural network (ANN) solutions to find efficient feature maps with the purpose of dimension reduction. From among the most commonly-used ANNs used for this purpose, one can name self-organizing maps (SOM) [29] and autoencoders [30] as unsuper- vised networks, also convolutional neural networks (CNNs) [31] and the recurrent neural networks (RNNs) [32] as supervised solutions.

IV. Applications in Neural Signal Processing

In the context of neural signal processing, the transforms are usually employed for (a) spike detection, (b) spike sorting, and (c) data compression. In this chapter, these applications will be discussed.

A. Spike Detection

To extract spikes from noise background noise, spike detection is inevitable. Spike detection is usually realized by comparing the neuronal signal amplitude with a threshold value. Once the signal amplitude exceeds the threshold value, the occurrence of a spike is detected. Employment of proper data transformations can help more effectively achieve this goal by enhancing the discrimination between neuronal spikes and the background noise. The wavelet transform with a wide variety of basis functions is among the most commonly-used transforms for spike detection. Digital Haar wavelet transform (DHWT) has been previously suggested for this purpose. To improve signal-noise discrimination, the Coiflet [33], biorthogonal [34], Mexican-hat [35], Daubechies4 [36], and Daubechies8 [37] wavelet families have been proposed as other alternatives.

Alternatively, taking into account the differences in frequency characteristics of the signal and the noise, mathematical transforms such as Hilbert transform [21], Haar transform [38], Walsh transform [39], integral transform [40], and the derivative transform [15] have been suggested to enhance the accuracy of spike event detection. Besides, the TEO is one of the most popular transforms used for spike event detection [41]. The TEO transform is employed to measure the rapid variations in the signal energy associated with neuronal spikes [18]. Furthermore, MTEO is suggested to improve the computational complexity.

B. Spike Sorting

It is known that the spikes originating from the same neuron are all of a similar waveform. Spike sorting in neuroscience literature is the process of isolating such spike waveform classes. As efficient feature extraction techniques, mathematical transforms have been used to discriminate spike classes from one another. For this purpose, the Fourier transform is used to separate spike waveforms based on their frequency characteristics [42]. A variety of wavelet families are also used to perform time- frequency analysis for feature extraction, helping improve class discrimination. Using the separability analysis [43], the 4-level Haar wavelet transform is suggested for the extraction of proper discriminative features [44]. Moreover, other wavelet functions are suggested for feature extraction, namely Daubachies2 [45], Daubachies4 [46], Daubechies8 [37], Symmlet4 [47], Symmlet8 [48], Coiflet3 [49], Coiflet5

[33] and Cohen–Daubechies–Feauveau 9/7 (CDF97) [35]. Furthermore, derivative transforms of different orders (as well as inverse derivatives [50] and varieties of integral transforms [51]) are used for the advantages they exhibit in feature extraction, the most notable of which is their noise shaping property [52].

C. Data Compression

The number of sites on recording electrodes has been doubled every seven years [3] and is expected to keep increasing at the same pace. Consequently, the data volume acquired by neural recording is supposed to increase exponentially. Compression of recorded data through the elimination of redundant data and preserving the informative contents is, therefore, an effective method for handling such data. In neuronal signal processing, data compression is generally achieved through two steps: first, compaction of the data representation, and then taking a procedure to reduce the volume of the bits conveying useful signal contents. For the first step, data transformations have been effectively used to provide minimal or compact representations for the data associated with neuronal activities. The wavelet transform is a successful family of transformations in mapping neuronal data to compact target space. Due to their general similarity to spike waveforms, Daubechies4 and Symmlet7 were suggested as proper basis functions for compressing and even denoising neural signals [53].

Because of the non-uniform frequency content of neuronal signals, the Walsh-Hadamard transform (WHT) [54], the discrete cosine transform (DCT) [55], and the discrete Tchebichef transform [56] are also considered as proper choices for neuronal data compression. In addition to the aforementioned transforms, compressive functions such as the exponential function [57] and the simple difference operator [17] have been embedded in the hardware of neural recording systems for data compression purposes.

As mentioned above, following the compaction step, the compact data usually goes through a reduction process. In the majority of neuronal data compression techniques, data reduction is achieved through one of the following procedures: (i) subsampling; being the selection of a subset of samples. This can be realized by either downsampling or extracting certain parts of the signal (e.g., neuronal spikes) [58]. (ii) subquantization; that is the selection of a subset of bits in each sample. This is done in different ways, including rounding truncation [58] and vector quantization [59]. (iii) encoding; referring to making a change in how the data stream is coded in such a way that the resulting codewords become of shorter effective length. Run-length-encoding (RLE) [54] and entropy coding [60] are the most common encoding techniques that have been used for this purpose.

V. Conclusion

In this paper, we have reviewed the transformations in neural signal processing. Firstly, the neural signal and corresponding processing are introduced. Then we discussed some transformations employed in neural signal processing, which could be categorized into time-domain analysis, frequency-domain analysis, time-frequency analysis and other transformations. Finally, we discussed the applications of the transformations in neural signal processing. The goal of this paper is to sort the transformations in neural signal processing which could help to understand the brain activities more vividly and deeply.

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