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Neural signal compression using a minimum Euclidean or Manhattan distance cluster-based deterministic compressed sensing matrix

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ABSTRACT

Multichannel wireless neural signal recording systems are a prominent topic in biomedical research, but because of several limitations, such as power consumption, the device size, and enormous quantities of data, it is necessary to compress the recorded data. Compressed sensing theory can be employed to compress neural signals. However, a neural signal is usually not sparse in the time domain and contains a large number of similar non-zero points. In this article, we propose a new method for compressing not only a sparse signal but also a non-sparse signal that has identical points. First, several concepts about the identical items of the signal are introduced; thus, a method for constructing the Minimum Euclidean or Manhattan Distance Cluster-based (MDC) deterministic compressed sensing matrix is given. Moreover, the Restricted Isometry Property of the MDC matrix is supported. Third, three groups of real neural signals are used for validation. Six different random or deterministic sensing matrices under diverse reconstruction algorithms are used for the simulation. From the simulation results, it can be demonstrated that the MDC matrix can largely compress neural signals and also have a small reconstruction error. For a six-thousand-point signal, the compression rate can be up to 98%, whereas the reconstruction error is less than 0.1. In addition, from the simulation results, the MDC matrix is optimal for a signal that has an extended length. Finally, the MDC matrix can be constructed by zeros and ones; additionally, it has a simple construction structure that is highly practicable for the design of an implantable neural recording device.

1. Introduction

Over the past several years, neural recording and stimulation systems have contributed substantial benefit to patients who suffer from Parkinson's disease, major depressive disorder, and epilepsy [1,2]. However, research and applications demand an increasing number of requirements, which implies more requirements for the neural recording system. These requirements include having high-density integration of the recording electrodes [3,4] (now, to our knowledge, a neural recording system can integrate more than a thousand electrodes [5]), low temperature (an increase in the temperature of the cortex must be smaller than one centigrade, which means that the maximum power density should be 0.8 mW/mm^2 for the exposed tissue area [6]), long device lifetime, and small device size. Among all of these requirements, the power consumption is one of the most challenging issues. In a patient who requires an implantable medical device, there must be limit to the frequency of replacing the batteries to both reduce the cost of the surgeries and improve the quality of life. For example, if there is a portable battery that has an energy density in the range of 1 $W\text{-}h/cm^3$, a battery volume on the order of 10 μW average power per cubic centimeter is required for a 10-year device life span [7]. Moreover, many of the implantable devices integrate a wireless transmission part, which aggravates the situation of having stringent energy constraints, because large amounts of recorded data required a very high carrier frequency, which substantially increases the power consumption of the device [8–10]. A common ultra-wideband (UWB) radio exhibits energy-efficiencies in the nJ/bit range, whereas the power consumption of the other components is 10^3 times less than that of the UWB radio [7]. Therefore, a data reduction strategy for an implantable device should be employed to minimize the power consumption of the system.

Most of existing methods for implementing integrated data compression under these constraints involves detecting neural spikes [11,12] or extracting the data features of the signal [13,14]. However, both of these methods cause distortion or loss of the data information. For example, in a neural spike-detection recorder, the data are obtained only in a time series or as an impulse signal but

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not as the signal itself [15]. If the thresholds of the detection are not properly set, then the spikes cannot be detected. At the same time, the feature extraction requires a period of time to train. Based on this method, the precision usually cannot be guaranteed, and the hardware design is also complicated [16]. Therefore, we must find a new method that does not lose the details of the signal to accomplish the goal of recording the signal.

Compressed sensing (CS) technology gives us a new choice for signal compression. In recent years, this approach has attracted considerable attention in the areas of computer science, applied mathematics and electrical engineering [17,18]. CS constitutes a revolution over the traditional Nyquist sampling frequency (Shannon theory). CS technology can be divided into three main parts: sparse signal, signal reconstruction and sensing matrix.

1.1. Sparse signal

CS theory is based on the sparsity of the signal. If a signal Y, which can be found in a basis such as $V=[v_1, v_2, v_3, \ldots, v_n]$ has a sparse representation, then the signal is called a sparse signal. Specifically, suppose Y can be described as in the following equation:

$$Y = VX \quad \text{or} \quad Y = \sum_{i=1}^{n} x_i v_i \tag{1}$$

where x_i is the coefficient vector for Y under the basis V. If Y is sparse, then the coefficient x_i must be almost zero or negligible, and as a result, they can be omitted without any loss.

If a signal is sparse under some basis, then it can be regarded as a compressible signal. Usually, a signal is not sparse, but if the basis can be changed, then the sparse representation under the new basis can be obtained. For example, a sine wave is not sparse in the time domain, but it is sparse in the Fourier domain.

1.2. Signal reconstruction

There are many reconstruction methods; an example is the ℓ_1(or ℓ_2) norm-based reconstruction method, which searches for the minimum ℓ_1(or ℓ_2) value to construct the signal [19,20]. This type of algorithm includes the basic pursuit algorithm (BP), match pursuit algorithm (MP), orthogonal matching pursuit algorithm (OMP) [21,22], and threshold-based method (such as the iterative hard or soft thresholding algorithm [22,23]). Probability-based reconstruction methods constitute another type; for example, the sparse Bayesian method uses the maximum likelihood to reconstruct the signal [24,25]. As of now, it has been proven that for a k-sparse signal, if the order of the measurement is $2k$, the original signal can be recovered exactly [26].

1.3. Sensing matrix

Not all of the signals are sparse, and the "sparse" basis is usually difficult to find. Although the "sparse" basis of a signal can be found, how to implement it into a device is still difficult [27]. To compress the non-sparse signal, we introduce a new concept for the compressed sensing, which is that not only the zero points in a signal can be compressed but also the identical non-zero points in the signal can be compressed. Therefore, in this article, we construct a deterministic sensing matrix that is based on this idea to compress the neural signals.

The sensing matrix can be divided into two types: random and deterministic matrices. Currently, most of the designers use a type of random matrix as a sensing matrix in the system, such as the sub-Gaussian sensing matrix [7,15] or the random discrete Fourier transmission matrix [28]. However, the random matrix has disadvantages. First, storing the random matrix requires a large amount of space, and the effectively proven random sensing matrices require items with superior randomness, which causes there to be stringent requirements for the design of a random number generator. Moreover, a random number generator aggravates the complexity of the hardware design, especially for an implantable device, because the generator usually has large power consumption and a large silicon area. Therefore, the current random sensing matrices are not the best choice for an implantable hardware design.

In addition, a deterministic sensing matrix is discussed as an optional type of sensing matrix. The advantage of the deterministic matrix is that it can generate the items of the sensing matrix on the fly without storing the data, and it is also easy to reconstruct the original signal. However, current deterministic sensing matrices, such as the Discrete Chirp sensing matrix [29], the Reed Muller sensing matrix [30], and the BCH sensing matrix [31], are also complicated with respect to the hardware implementation, and they cannot be used for a non-sparse or low-sparse signal; although a low-density parity-check (LDPC) matrix contains only 0's and 1's, the compression of a non-sparse or low-sparse signal requires a very high-girth sensing matrix that is very difficult to generate [32,33]. Therefore, a novel deterministic sensing matrix must be constructed.

Moreover, there are two important contributions in this article. First, we use the similarity that is in a signal to construct the compression. In fact, a specific neural signal may contain many identical (or similar) points, and traditional compressed sensing concerns only the zero items in a signal; it does not concern two identical (or similar) non-zero points in the signal. Therefore, we research these identical or highly similar non-zero points, i.e., the similarity of the points in a signal, from the perspective of compressed sensing theory. Additionally, we use the advantages of the deterministic sensing matrix to construct a sensing matrix that is based on the clustering of the neural signal itself. In brief, the primary contribution of this article is that we design a deterministic compressed sensing matrix to compress non-sparse or low-sparse signals that have identical non-zero points, and the compressed signals can be largely recovered.

To illustrate our work, we give definitions and proof for the MDC sensing matrix in Section 2. We introduce the dataset of the simulation in Section 3. The simulation results and a discussion based on the MDC sensing matrix are given in Section 4. Finally, in Section 5, we provide a conclusion.

2. Minimum Euclidean or Manhattan distance cluster-based deterministic sensing matrix

First, we provide the definitions of several basic concepts and the method of MDC matrix construction. (Some important variables or symbols are illustrated in Table 1).

The most important concept in compressed sensing theory is the Restricted Isometry Property (RIP), which is shown as follows.

Restricted Isometry Property An $M \times N$ sensing matrix Φ is said to satisfy the Restricted Isometry Property of order k if it satisfies the following equation:

$$(1-\varepsilon_k)||X||_2^2 \quad \leq \quad ||\Phi X||_2^2 \quad \leq \quad (1+\varepsilon_k)||X||_2^2 \tag{2}$$

for all of the k-sparse vectors X. The restricted isometry constant ε_k of matrix Φ lies between 0 and 1. The restricted isometry constant ε_k, $k \in (1,n)$ of sensing matrix Φ is defined as below:

$$\varepsilon_k(\Phi) = \max_{|T|\le k} ||\Phi_T^* \Phi_T - I_{\mathbb{R}^T}|| = \max_{|T|=\lfloor k \rfloor} ||\Phi_T^* \Phi_T - I_{\mathbb{R}^T}|| \tag{3}$$

where the maximum is over all of the subsets $T \subseteq [n]$ with $|T| \le [k]$ or $|T| = [k]$, and Φ_T means all $M \times k$ sub-matrices of Φ.