Online Calibration of Intracortical Neural Interface Based on Transfer Learning

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Abstract. In the application of neural interface, the neural activity of neurons and neuronal groups is not fixed even under the same task conditions. Meanwhile, the recording conditions of neural signals are also very unstable, with a high degree of within- and across-day variability. This results in a very unstable firing pattern for the recorded neural spike signals. In order to get better performance, the decoder often requires a lot of online calibration samples. This brings a heavy training burden to neural interface users. To solve this problem, this paper proposes to apply transfer learning (TL) to online calibration of intracortical neural interface to reduce the dependence of decoder on a large number of online calibration samples. Experimental results show that through transferring from a large amount of historical data, decoder can achieve satisfactory classification accuracy with only a small amount of online data.

1. Introduction

The neural signals used commonly in neural interface include electroencephalo-graph (EEG) signals, peripheral nerve signals (PNS) and cerebral cortex neural signals (CNS). Among them, the neural interface based on cerebral cortex neural signals is an important research direction. Although the acquisition of cerebral cortex neural signals is invasive, the neural spike signals obtained in this way have the minimal noise and the most relevant information. Therefore, this type of intracortical neural interface has drawn much attention from researchers and has an important clinical significance [1]. Currently, primates have been able to perform some 3-D actions using neuroprosthetics through neural interfaces, such as controlling computer cursors [2], self-feeding [3]. Research on human neural interface has also made breakthrough progress. At present, paralyzed patients can complete such movements as controlling computer cursors [4] and even drinking coffee [5] with neuroprosthetics.

Currently, many linear or non-linear algorithms have been used in decoders for neural spike signals, such as K-nearest neighbors (KNN), Support Vector Machine (SVM) [6], and Kalman Filtering [7]. However, studies have shown that neural activity generated by neurons and neuronal groups is not fixed, even under the same task conditions. In addition, taking into account the clinical application of neural interface, the recording conditions of neural signals are also unstable, with a high degree of within- and across-day variability [8]. This leads to the traditional decoder algorithm cannot deal with the continuous changes of recording conditions. Usually, a large number of online samples are required to recalibration the decoder. Collecting a large number of calibration samples takes a lot of...
time and effort, which brings a heavy training burden to neural interface users and is unbearable for many paralyzed patients. In view of this, we hope to find a suitable method which can ensure the decoder's performance while reducing the demand for online calibration samples.

Several researchers have begun to introduce transfer learning to EEG-based brain-machine interfaces. Wang et al. [9] classified these approaches into three types based on the learning strategy: feature representation transfer, instance transfer and classifier transfer. Feature representation transfer encodes discriminative information across subjects or sessions into a new feature representation [10][11]. In instance transfer, discriminative information across subjects and sessions is transferred by adding weights to the data from the source domains [12][13]. Classifier transfer mainly includes domain adaption of classifier [14][15] and ensemble learning of classifiers [16]. But no transfer learning research about cerebral cortex neural signals has been performed. This work applies TL in the online calibration of an intracortical neural interface system to reduce the dependence of the decoder on a large number of online calibration samples by transferring discriminative information across sessions.

2. Method

2.1. Experiment Description

A male monkey named Astra was trained to perform a 3-D reach-to-grasp task using the right hand. The experimental apparatus (Figure 1(a)) consists of a horizontal center holding pad and two rectangular targets around the height of the monkey's shoulders. These two targets are labeled "Target 01" on the left and "Target 06" on the right. We can use high-speed programmable servo motor to quickly change its angle, variable angles are 45 °, 90 ° and 135 °. Each target is equipped with touch sensors on both sides to detect whether the monkey is grasping the target. A successful trial is produced by grasping the target firmly using a powerful grip, making contact with both sensors.

The sequence of events for the reach-to-grasp task is shown in Figure 1(b). The monkey was seated on a fixed chair in front of the experimental apparatus, and the left arm was fixed. Each trial started with the central indicator light on, cueing the monkey to place its hand on the central holding pad. After a random central pad touch time (CHT, 300 ~ 700ms), the central indicator light goes out, and a target light came on, cueing the monkey to reach for the indicated target and make a whole hand grasp. The time from target light on to central pad release was the cue reaction time (CRT). And the time from central pad release to target hit was the movement time(MT). The target light would go off after a target hold period. The monkey would release the target and put the hand on the central pad to wait for the next trials. The two targets remained parallel and the two target lights were illuminated in pseudo-random order of the same probability. The monkeys would receive a drop of water as a bonus after a successful trail. The Institutional Animal Care and Use Committee approved the behavioral paradigm, surgical procedures and animal care.
2.2. Data Collection

A recording-chamber was implanted in M1 (contralateral hemisphere) of monkey Astra to record the neural activity that the monkeys performed the 3-D reach-to-grasp task. A multi-electrode micro-drive (Thomas Recording, Germany) was used to insert five independently controllable microelectrodes (quartz-insulated platinum-tungsten electrodes). Each electrode made one penetration a day, and the penetrations covered the hand representation area of M1, some of PMd and PMv. In order to record more neurons, we would change the depth of the recording electrode after we completed every 108 successful trail (54 trials to each target condition).

2.3. Neural Signal Preprocessing

The neural signals were recorded by Plexon system (Plexon, Inc.) and sampled at 40 kHz/channel. We could isolate up to 4 units on each single channel using the waveform discrimination, and a threshold crossing marked the occurrence of a sorted action potential (spike). After a recording session, units were checked and re-sorted offline using Offline Sorter (Plexon, Inc.) on all of the channels using template matching or waveform-feature detection algorithms combined with principle component method.

2.4. Feature Extraction

We analyzed the 100 ms before Central Pad Release and the 200 ms after Central Pad Release (a total of 300ms). The spike trains of each neuron at analysis time were divided into 3 non-overlapping and equally-sized bins, where each bin was 100 ms in length. Then, the spike rate of each neuron in each bin was calculate, so that each neuron can get 3 features. Assuming that features was extracted from m neurons, a total of 3*m features can be obtained for each trail. These features form the feature vector $x$. 

Figure 1. Experimental apparatus. (a) Top view of the experimental apparatus. Target 1 and Target 6 are the two reach-to-grasp targets. (b) Sequence of events for the reach-to-grasp experiment. The duration between the time when a certain target indicator light comes on and the time when central pad release occurs is denoted by CRT. The duration between the time when central pad release occurs and the time when the target hit occurs is denoted by MT.
as in equation (1), where \( x_{ij} \) denotes the spike rate in the \( j \)th bin of the \( i \)th neuron, \( i = 1, 2, \ldots, m \), \( j = 1,2,3 \).

\[
\mathbf{x} = \left( x_{11}, x_{12}, x_{13}, x_{21}, x_{22}, x_{23}, \ldots, x_{m1}, x_{m2}, x_{m3} \right)^T
\]

(1)

2.5. Transfer Learning

In our case, each session corresponds to a feature subspace of the feature space. A new session is randomly selected as the target domain, and the remaining sessions are seen as the reference data of multiple source domains. Because each session uses the same feature extraction method, they can be considered to be in the same feature space. But the data distribution varies across sessions.

The algorithm used in this paper [17] belongs to inductive transfer learning [18]. The algorithm framework is shown in Fig.3. A total of 9 sessions were used in the experiment, of which one session was randomly selected as the target domain, the remaining eight sessions were seen as multiple source domains. First, a sub-classifier \( C_0 \) was trained by using a small number of samples of the target domain. Then the samples of each source domain was mixed with the samples of the target domain, and a sub-classifier \( C_i \) is trained by using the mixed data. Finally, these sub-classifiers were integrated by weighted voting, where the weight of \( C_0 \) was \( 1 \), and the weight of \( C_i \) was its cross-validation accuracy. For a sample \( x \), if the prediction function of \( C_i \) is \( f_i(x) \), then the final prediction function is as

\[
f(x) = \text{sign} \left( f_0(x) + \sum_{i=1}^{n-1} a_i f_i(x) \right)
\]

(2)

![Figure 2](image)

Figure 2. Target is the dataset of the target domain. Source \( i \) is the dataset of source domain \( i \), where \( i=1, 2,\ldots, (n-1) \). Mixed data \( i \) is the mixed dataset composed of Target and Source \( i \). Classifier \( i \) is the sub-classifier trained on Mixed data \( i \). Classifier 0 is the sub-classifier trained on Target, \( a_i \) is the cross-validation accuracy of Classifier \( i \) on Mixed data \( i \).

3. Experiment Result

The transfer learning algorithm used in this paper is based on the multiple source domains sample, but only one monkey was used in the experiment, so we considered the datasets of multiple neural groups collected with acute neural electrodes as the datasets of multiple source domains. There were 9 sessions of data, and each session contains 108 trials (54 in each direction, a binary classification problem). Each session corresponds to a different record location of M1, which records the information of neural activity of a neuron group. The spike response of these different neuron groups followed different data distributions. For the 9 session datasets, a session was selected as the target domain dataset and the remaining 8 sessions as the source domains datasets. This process was repeated
9 times, and each session was traversed and used as the target domain dataset. Only a small amount of samples from the target domain dataset was used to simulate the current calibration samples for decoder, and the remaining samples were used for test samples. In order to take full advantage of the data from eight source domains, all samples of each source domain dataset were used by TL. Only 5 neurons were used to extract features. In order to evaluate the performance of the TL algorithm, we chose two baselines for comparison.

BL1: The decoder is trained using only a small number of samples from the target domain.

BL2: The decoder is trained using a direct mixture of all the samples from the source domains and a small number of samples from the target domain.

The BL1 uses only a small number of samples from the target domain (2 to 20) to train the model, which is equivalent to the neural interface users only completing a small amount of calibration tasks. In clinical applications, neural interface users often cannot afford a lot of calibration tasks. The samples used by the BL2 are the same as those used by TL, but the BL2 mixes a small sample of the target domain directly with a large number of samples from the source domain to train the decoder. By comparing with the BL1 and the BL2, the performance of the TL algorithm can be evaluated.

The sub-classifier algorithm of transfer learning (TL) uses support vector machine and the kernel function is linear kernel function. Figure 3 shows the average performance of the TL algorithm on the nine sessions.

**Figure 3.** Average performance of the TL algorithm on the nine sessions. Abscissa: number of calibration samples from the target domain. Ordinate: classification accuracy of the decoder on the test data.

Figure 3 shows that the TL performs significantly better than the BL1 and the BL2. Compared with the BL1, particularly when there are very few calibration samples from the target domain (2-4 samples), the TL can improve the accuracy of the decoder by nearly 10%. If the target domain calibration samples continuously increase, the extent to which the TL algorithm improves the accuracy of the decoder decreases slightly but still remains at approximately 5%. This demonstrates that the TL algorithm can effectively use a large number of reference samples from multiple source domains to train the current decoder and only requires a small number of online calibration samples from the target domain to train a satisfactory decoder, which is of great significance to the clinical application of neural interface. It can be seen from Figure 3 that the classification accuracy of TL is 73.46% when the number of target domain calibration samples is 6, but 20 target domain calibration samples are required for BL1 to achieve the same accuracy, i.e., 70% less calibration training is required for the decoder to achieve this classification accuracy when the TL algorithm is used compared with the BL1.
When the number of calibration samples increase to 20, the classification accuracy of TL can reach 77.73%, but 50 target domain calibration samples are required for the BL1 to achieve the same accuracy, i.e., a 60% less calibration training is required. In other words, historical data from the current user or even other users can be effectively used through TL to train the decoder, and the current user only needs to train a few times to obtain a neural decoder with good performance. Thus, TL can significantly reduce the training burden on the current user of a neural interface and improve the user experience.

4. Conclusions
We apply one TL framework in the online calibration of an intracortical neural interface and, by TL, effectively use a large number of samples from the source domains. As a result, we only need to use a small number of samples from the target domain to improve the classification accuracy of the decoder on the target domain. The TL algorithm used in this work is effective for all of the nine sessions. In particular, when there is a very small number of samples from the target domain, the decoder that is completely based on online samples shows almost no classification ability, and the classification performance of the decoder based on a direct mixture of online and auxiliary samples is also very poor. In comparison, the TL algorithm effectively uses a large number of samples from the source domains to dramatically improve decoder performance. In addition, the TL algorithm also reduces the amount of times required for online training by at least 60%, which is of great significance to clinical applications of neural interfaces. In clinical applications, we can take full advantage of historical data or even data from other users to obtain a high-performance neural decoder without requiring the current user to perform a large amount of calibration training.

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