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Methodologies on Brain-Machine Interaction

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Abstract: Recent development in cognitive neuroscience and brain imaging technologies provides us with a increasing ability to a new multidisciplinary research, brain machine interactions (BMIs). In this paper, the critical technologies used in BMIs, such as bio-sensor, translation algorithms, and the major applications are discussed. By providing an overview of these aspects, we can see how advanced technologies in these areas can be utilized to improve the state of art BMIs. In this paper, based on real EEG data, RBF neural network method and a machine learning algorithm, weighted locally linear embedding (WLLE) are proposed for neural modeling and pattern recognition respectively to efficiently interpret brain patterns for BMIs.

1. INTRODUCTION

Advances in cognitive neuroscience and brain imaging technologies provide us with the increasing ability to interact directly with activity in the brain. During the recent decade, the research on direct functional interfaces between brains and artificial devices, such as computers or artificial robot limbs, have succeeded so readily that a new multidisciplinary area, brain machine interactions (BMIs), could be developed based on the frontier of systems neuroscience, bio-sensing, computing, electronics, mechachonics and communications technologies with the potential to act as intelligent and high-level communications and with important applications in clinic, prostheses, entertainment, games and health maintenance.

Since the first experimental demonstration presented in (Chapin et al. [1999]) that a robotic manipulator could be directly controlled by ensembles of cortical neurons, a continuous stream of research papers have shown an enormous interest in BMIs among the scientific community. Several groups of researchers have successfully used BMIs for controlling computer cursors, wheelchair or other devices, and helping paralyzed or action constrained patients to communicate with outside as described in (Wolpaw et al. [2002], Birbaumer et al. [1999], Hinterberger et al. [2005], Kubler et al. [2001a,b], Obermaier et al. [2003, 2001], Sheikh et al. [2003], Wolpaw [2004], Birbaumer [2006]).

Born as a highly multidisciplinary field, the BCIs lies in the extremely rich information provided by a lot of distinct areas of researches:

(i) the brain sensing technologies as an input mechanism that can be mapped into BMIs commands for controlling should be full developed;
(ii) the cognitive mechanisms on the user involved tasks should be thoroughly analyzed and evaluated to develop translation algorithms from brain activities to command signals; and
(iii) cognitive and affective state of the user should be dynamically adapted to evaluate the interaction between human and machine.

Successful research and development in the area of BMIs have important implications in several aspects of human society. Developed with bio-sensor technology, cognitive science, intelligent control, and efficient translation algorithm, the BMIs can act as a high level communication to users from diverse groups, e.g., as prostheses for handicapped people, or a fun controller in video games for entertainment of common population. These thrusts enable the development of human-machine interactions that adapt dynamically to human intentions, emotions, and needs, and bridge the gap between the three spaces: human space, physical space and information space.

In this paper, we briefly review the latest advances in the core technologies of the BMIs. Then RBF neural network method for modeling and a machine learning algorithm, weighted locally linear embedding (WLLE) for clustering an EEG data set are presented and applied in a case study. In the following sections, we first introduce the up to date bio-sensor technologies in Section 2. Then the translation algorithms for obtaining command signal from the brain activities are discussed in Section 3. A series of different BMI applications are introduced in Section 4. Furthermore, in Section 5, RBF neural network and WLLE algorithm are presented, and a case study is carried out for modeling and clustering a data set with two type brain patterns, left hand movement and right hand movement. At last, conclusion is given in Section 6.

2. BIO-SENSORS FOR BMIS: MONITORING AND RECORDINGS OF NEURONAL ACTIVITY

During the past decade, a number of BMIs or BCIs have been developed based on different bio-sensor technologies for monitoring and recording brain activity, and can be

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classified into two main classes by the feature of invasive or noninvasive.

The invasive methods appeared first as part of an evaluation for epilepsy surgery, when it is necessary to insert electrodes near the surface of the brain, under the surface of the dural matter, which is accomplished via burr hole or craniotomy. This is referred to variously as "electrocorticography (ECoG)", "intracranial EEG (I-EEG)" or "sub-dural EEG (SD-EEG)". Recently, many researches on BMIs are based on the intracranial sensor methods due to its capacity and high transfer rate (Obermaier et al. [2003], Wolpaw and McFarland [2004]).

There are also a variety of noninvasive methods that have been employed to monitor brain signals in BMIs. They include, but are not limited to: electroencephalographic signals (EEG), magnetoencephalographic signals (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and optical imaging (NIRS, near-infrared systems). Among these methods, EEG seems to have the three properties that could lead to successful implementation of BMIs for various missions: noninvasiveness, relatively low cost, and portability. The main features such as spatial solution, time solution, hardware complexity and cost of different technologies are demonstrated in Fig. 1 according to the descriptions in (Volkow et al. [1997], Casey and Haan [2002], Purves et al. [1999]).

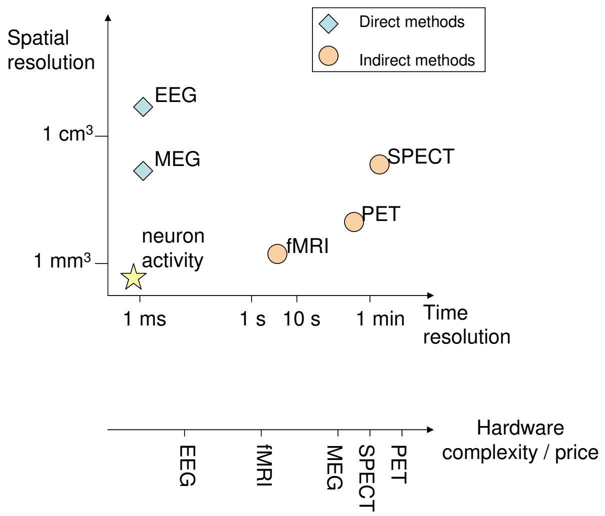

Fig. 1. Overview of the core technologies involved in brain signal sensing

3. TRANSLATION ALGORITHMS: FROM NEURONAL ACTIVITY TO COMMAND SIGNALS

At present, BMIs use a variety of translation algorithms for obtaining the features to communicate with the intent of the user. Slow cortical potentials (SCPs), a potential shifts in EEG around 1-2 Hz, which can be controlled by humans using feedback and positive reinforcement mechanism, are introduced and utilized in (Kubler et al. [2001b], Birbaumer et al. [2000]). The third positive component in visual evoked potentials that evoked around 300 ms after visual stimuli, which called P300 evoked potentials, are utilized for several BMI applications in (Donchin et al. [2000], Piccione et al. [2006], Sellers and Donchin [2006]). mu rhythm, which is alpha-range activity that can be seen over the sensorimotor cortex, has been studied in (McFarland et al. [2004], Wolpaw and McFarland [2004]). Steady state visual evoked potential (SSVEP) in (Lalor et al. [2005], Sutter [1984]) and event-related synchronization (ERS), event-related desynchronization (ERD) via motor imagery in (Pfurtscheller et al. [2003], Pfurtscheller and da Silva [1999]) are also popular methods used in BMIs.

Among these translation algorithms for obtaining command signals from neuronal activity, SCP requires extensive training, but once mastered, it will have a relatively stable performance. Methods such as P300 VEP, do not require training but need many trials of signal with low response. Another method, motor imagery, has fast response but the performance is not satisfactory. SSVEP has been successfully used with only one active channel, however, it requires users to gaze at flashing blocks, which make it not practical for long time using. There is still no perfect translation algorithm for all type of BMIs, that's to say, which way is better depends on the object of BMI and many other practical aspects.

4. DIFFERENT APPLICATIONS OF BMIS

BMIs enable communication without movement. Most BMI researches focus on restoring communication for severely disabled people, these include prostheses with haptics such as in (Birbaumer and Cohen [2007], Birbaumer [2006], Birbaumer et al. [2000, 1999], Light et al. [2002], Navarro et al. [2005]), wheelchair controlled by mind in (Philips et al. [2007], Rebsamen et al. [2007]), and so on. BCIs may also be helpful for treating brain disorders and mental diseases, such as stroke, autism, epilepsy and emotional disorders in (Sterman et al. [1974], Fox [1999], Lubar et al. [1995], Pfurtscheller et al. [2003], Pfurtscheller and da Silva [1999]). In (Pan et al. [2007b]), we proposed a statistic method for detecting seizures onset based on the EEG signal. To further improve the diagnosing performance, we proposed a machine learning algorithm, weighted locally linear embedding (WLLE), and utilized it for unsupervised feature extraction, which shown better performance than some other manifold learning algorithms.

Although BCI and BMI researches will likely continue to focus on medical applications, they may be also useful to healthy users for other applications, such as playing video games by mind, controlling robot remotely, flight/space training for pilots and astronauts (Kong et al. [2002]), substituting traditional interfaces such as keyboard, mice, and controlling virtual and real machines (Lalor et al. [2005], Obermaier et al. [2003], Bayliss and Ballard [2000], Roux et al. [2003], Chapin et al. [1999]). An intelligent environment including control TV, light, air conditioner, etc. by mind for both the physically handicapped and healthy people was developed by Cyberkinetics.

5. A CASE STUDY

In this section, we aim to analyze some EEG data associated with either a left finger movement or a right finger movement. The real EEG data we used are generously provided by Fraunhofer-FIRST, Intelligent Data Analysis Group (Klaus-Robert Müler), and Freie Universität Berlin, Department of Neurology, Neurophysics Group (Gabriel Curio), through the BCI Competition 2003 website (Blankertz et al. [2003, 2002]).

The Berlin Data were collected from 28 EEG sensors as the subject moved either his left or right index finger in succession 316 times at his own pace. Only the data for the 500ms before the finger movement were used, thus these data represent the mental activity about finger movement of the subject. These data are expressed as a 50×28 matrix for each trial, and the whole data set contains 316 trials.

In this case study, we first use Radial-Basis Function Neural Network (RBFNN) to model the brain patterns to show the potential of artificial neural network (ANN) for identifying the brain activities. Then an unsupervised manifold learning algorithm, weighted locally linear embedding (WLLE) is utilized for extracting features and clustering the 316 EEG trials into two clusters, between which one represents the left finger movement and the other is a representative of the right finger movement. This successful clustering algorithm can then theoretically be implemented in a BMI/BCI to give some limited control over the computer or mechanic systems by directly thinking.

5.1 Dynamic Identification and Modeling of Brain Activity

A group of researches focus on understanding complex dynamics in biological brains by modeling and identification the temporal dynamical brain signal (Koch and Segev [1989]). The thorough understanding of the nonlinear brain dynamics and neurobiology may not only be helpful to the field of artificial intelligence for pattern recognition (Ge et al. [1992], Yao and Freeman [1990]), but also offer critical fundamental information for developing BMIs/BCIs.

In (Wu et al. [2004]), the authors presented a switching Kalman filter model for the real-time inference of hand kinematics from a population of motor cortical neurons which can cope with crudely sorted neural data common in on-line prosthetic applications. In (Yao and Freeman [1990]), a model of biological pattern recognition based on the observation of biological phenomena is proposed.

A series of systematic theories and applications for dynamic identification and modeling such as neuro-fuzzy identification (Jia et al. [2005]), biological system control (Pan et al. [2007a], Ge et al. [2005]), and machine learning algorithm (Ge et al. [2006a,b]) were developed.

The Radial-Basis Function Neural Network (RBFNN) is usually used as a tool for regression of nonlinear dynamics because of its good capabilities in function approximation. In this paper, the following RBFNN is used for modeling the dynamic brain patterns $h(Z)$: $R^q \to R$

$$h_{nn}(Z) = W^T S(Z) \qquad (1)$$

where the input vector $Z \in \Omega \subset R^q$, weight vector $W = [w_1, w_2, \ldots, w_l]^T \in R^l$, the NN node number $l > 1$; and $S(Z) = [s_1(Z), \ldots, s_l(Z)]^T$, with $s_i(Z)$ being chosen as the commonly used Gaussian functions, which have the form

$$S(Z) = \exp\left[\frac{-(Z-\mu_i)^T(Z-\mu_i)}{\eta_i^2}\right] \qquad (2)$$

where $\mu_i = [\mu_{i1}, \mu_{i2}, \ldots, \mu_{iq}]^T$ is the center of the receptive field and η_i is the width of the Gaussian function.

It has been proven that network (1) can approximate any continuous function over a compact set $\Omega_Z \subset R_q$ to arbitrary any accuracy as

$$h(Z) = W^{*T} S(Z) + \epsilon, \forall Z \in \Omega_Z \qquad (3)$$

where W^* is ideal constant weights, and ϵ is the approximation error.

The ideal weight vector W^* is an artificial quantity required for analytical purposes. W^* is defined as the value of W that minimizes $|\epsilon|$ for all $Z \in \Omega_Z \subset R_q$. When a good estimate, $\hat{W}$ is obtained, the nonlinear dynamics can be modeled and identified.

Fig. 2 shows two typical patterns of the Berlin data. One is labeled as upcoming left hand movements and the other is labeled as upcoming right hand movements. The modeling results for these two patterns using RBFNN are shown in Fig. 3. Figs. 2 and 3 show that the model is quite accurate and gives modeling patterns almost the same as the real patterns.

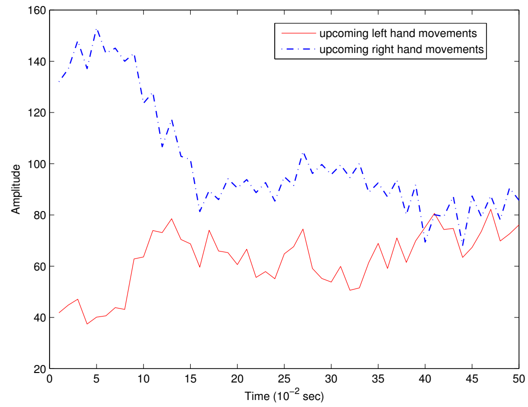

Fig. 2. Tow typical patterns of the Berlin BCI data

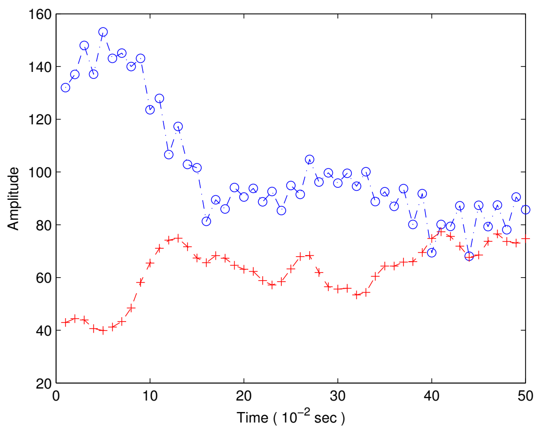

Fig. 3. Modeling of the two brain patterns

5.2 Unsupervised Clustering By Machine Learning

The Berlin data is expressed as a 50×28 matrix pattern for each trial, and the whole data set contains 316 patterns. We analysis this data set in two steps.

First, in each EEG pattern, there are 50 EEG samples, each of which contains 28 elements collected from 28 EEG channels. We could represent each pattern as $X = [x_1, x_2, \ldots, x_M]$, $M = 50$, where x_i is a state vector representing the spatial distribution of EEG signal at the *ith* sample point. For this 50×28 pattern matrix, we use the eigenvalues of its covariance matrix to form a pattern vector to represent the original matrix. The covariance matrix can be calculated as

$$C = \frac{1}{M}\sum_{i=1}^{M} x_i x_i^T \tag{4}$$

where $M = 50$ is the number of EEG samples in each pattern matrix X. Then, the eigenvalues of matrix C, λ_i, $i = 1, 2, \ldots, 50$, are calculated to form a pattern vector $\Lambda_i = [\lambda_1, \lambda_2, \ldots, \lambda_M]^T$ for each of the 316 EEG patterns.

The second step is dimension reduction (internal feature extraction) and clustering of the brain patterns. For the data set $\Lambda = [\Lambda_1, \Lambda_2, \ldots, \Lambda_N]$, $N = 316$ in the high dimensional space R^D, the goal of dimension reduction for feature extraction is to calculate a low dimensional embedding of the data into R^d where $d << D$, while keep the intrinsic structure of the original data set.

We first attempt to express data point Λ_i as a linear combination of its k nearest neighbors $\Lambda_j,\ j = 1, 2, \ldots, k$.

$$\hat{\Lambda}_i = \sum_{j \in \Omega_i} w_{ij}\Lambda_j \tag{5}$$

where Ω_i is the neighborhood of sample Λ_i. In the original LLE algorithm standard Euclidean metric based KNN is used to select the nearest neighbors. However, in the WLLE algorithm, we utilize the weighted distance measures in order to improve feature extraction performance.

The weighted distance is described in (Zhou and Chen [2006]) as follows,

$$Dist(\Lambda_0, \Lambda_i) = \frac{\|\Lambda_i - \Lambda_0\|}{a + b\frac{(\Lambda_i - \Lambda_0)^T\tau}{\|\Lambda_i - \Lambda_0\|}} \tag{6}$$

where $a + b\frac{(\Lambda_i - \Lambda_0)^T\tau}{\|\Lambda_i - \Lambda_0\|}$ is the weight of the distance from Λ_i to Λ_0.

To facilitate parameter estimation for weighted distance, we first present some properties in (Zhou and Chen [2006]).

Theorem 1. If a random vector Λ_i has a deformed distribution $D_d(a_i, b_i, \tau_i)$, then $E(\Lambda_i) = c_1 b_i \tau_i$ and $E(\|\Lambda_i\|) = c_2 a_i$, where c_1 and c_2 are constants.

$$c_1 = 2^{1/2}\frac{\Gamma((d+1)/2)}{\Gamma(d/2)d} \tag{7}$$

$$c_2 = 2^{1/2}\frac{\Gamma((d+1)/2)}{\Gamma(d/2)} \tag{8}$$

where Γ is the Gamma function $\Gamma(k) = \int_0^\infty t^{k-1}e^{-t}dt$, $(k > 0)$, and d is the low dimension of the embedding.

Then, we use its k-nearest neighbors $\Lambda_j,\ j = 1, 2, \ldots, k$ to estimate the parameters of the deformed distribution, that is, a_i, b_i and τ_i.

First, we calculate the difference between a sample Λ_i and all its k-nearest neighbors, $\Lambda_j,\ j = 1, 2, \ldots, k$, and obtain $V_i = [v_{i1}, v_{i2}, \ldots, v_{ik}]$, where $v_{ij} = \Lambda_j - \Lambda_i$. Then, we use $\hat{G}_i$ and $\hat{L}_i$, which are the center of mass and the averaged vector length of V_i:

$$\hat{G}_i = \sum_{j=1}^{k} v_{ij}/k, \qquad \hat{L}_i = \sum_{j=1}^{k}\|v_{ij}\|/k \tag{9}$$

to estimate $E(\Lambda_i)$ and $E(\|\Lambda_i\|)$, respectively. According to Theorem 1, we obtain an estimation to a_i, b_i and τ_i:

$$\hat{a}_i = \frac{\hat{L}_i}{c_2}, \qquad \hat{b}_i = \frac{\|\hat{G}_i\|}{c_1}, \qquad \hat{\tau}_i = \frac{\hat{G}_i}{\|\hat{G}_i\|} \tag{10}$$

After properly select the neighbors, the next step of WLLE is to obtain the optimal reconstruction weights for each neighbor point. The optimal weight matrix w_{ij} for data reconstruction can be obtained by minimizing the approximation error cost function

$$\epsilon(W_i) = \sum_i d_W(\Lambda_i, \sum_{j \in \Omega_i} w_{ij}\Lambda_j)^2 \tag{11}$$

subject to the constraints

$$j \notin \Omega_i \Rightarrow w_{ij} = 0 \tag{12}$$

$$\sum_{j \in \Omega_i} w_{ij} = 1 \tag{13}$$

where $W_i = [w_{i1}, \ldots, w_{ik}]$ is the weights connecting sample Λ_i to its neighbors, function $d_W(\cdot,\cdot)$ is an appropriate distance measure. The first constraint says that only data points in the neighborhood of data point Λ_i should be used in the reconstruction of $\hat{\Lambda}_i$, while the second constraint imposes invariance to translation.

The final step of WLLE is to compute a low dimensional embedding of the high dimensional inputs Λ_i based on the reconstruction weights w_{ij}. The high dimensional data are mapped into the low dimensional space R^d by requiring reconstruction to work as well as possible. This leads to another minimization problem. The low dimensional outputs y_i, $i = 1, 2, \ldots, N$ are found by minimizing the cost function,

$$\Phi(Y) = \sum_i d_W(y_i, \sum_{j \in \Omega_i} w_{ij}y_j)^2 \tag{14}$$

where $Y = [y_1, \ldots, y_N]$ consists of the data points embedded into the low dimensional space. This minimization problem is not well-posed without further constraints. Zero mean and unity covariance is used in this algorithm to make the problem well-posed. In other words Y should obey the constraints

$$\sum_{i=1}^{N} y_i = \mathbf{0} \tag{15}$$

$$\frac{1}{N}YY^T = \mathbf{I}, \tag{16}$$

where **0** is a vector with all elements being zero, and **I** is a identical matrix. The first constraint is to assure that coordinates y_i can be translated by a constant displacement without affecting the cost, while the second constraint imposes unit covariance of the embedding vectors.

Based on this algorithm we proposed, we calculated the 2D embedding of each brain pattern, and the result is shown in Fig. 4. The figure shows that the two type brain dynamics are clustered as two groups, where $*$ represent the right hand movement, $\circ$ is the left hand movement, thus the brain patterns related to left hand movement and right hand movement can be easily identified.

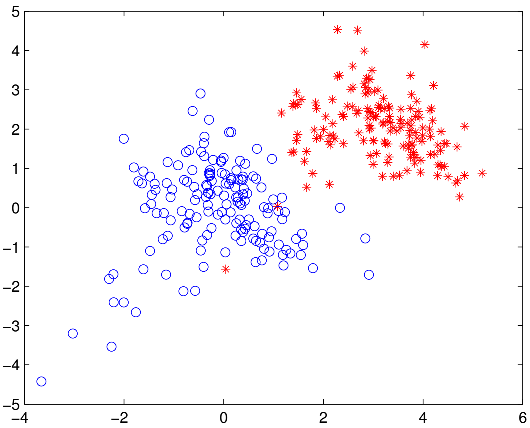

Fig. 4. Two clusters in 2D embedding of the brain dynamic patterns

6. CONCLUSION

In this paper, the critical technologies used in BMIs, such as bio-sensor and translation algorithm for brain computer interface (BCI) were discussed. The mainstream applications of BMIs in clinic, prostheses, entertainment, games and health maintenance were presented briefly. Potential of machine learning, dynamic modeling and identification for BMIs applications were demonstrated using a case study on real EEG data. By providing an overview of above aspects and a real data application, we demonstrated how advanced technologies in these areas can be utilized to improve the state of art BMIs.

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