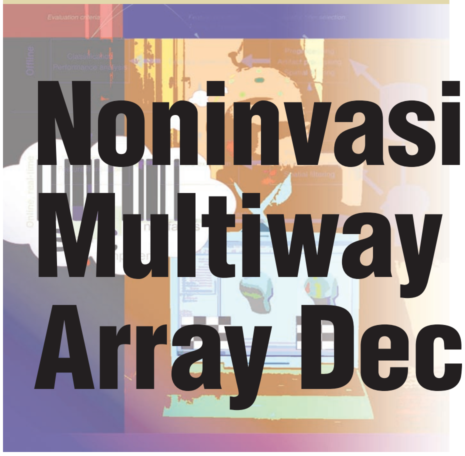

Noninvasive BCIs: Multiway Signal-Processing Array Decompositions

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In addition to helping better understand how the human brain works, the brain-computer interface neuroscience paradigm allows researchers to develop a new class of bioengineering control devices and robots, offering promise for rehabilitation and other medical applications as well as exploring possibilities for advanced human-computer interfaces.

Brain computer interfaces (BCIs) are systems that use electric, magnetic, or hemodynamic brain signals to control external devices such as computers, switches, wheelchairs, or neuroprostheses. While BCI research endeavors to create new communication channels for severely handicapped people using their brain signals, recent efforts also have been focused on developing potential applications in rehabilitation, multimedia communication, virtual reality, and entertainment/relaxation.[1-14]

The three major components of BCIs are:[2]

- ways of measuring neural signals from the human brain,
- methods and algorithms for decoding brain states/intentions from these signals, and
- methodology and algorithms for mapping the decoded brain activity to intended behavior or action.

Several existing brain monitoring technologies have been tested in BCI research for acquiring data—for example, electroencephalography (EEG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), and near infrared spectroscopy (NIRS). However, because MEG, fMRI, and NIRS are expensive or bulky, and because fMRI and NIRS present longtime constants in that they do not measure neural activity directly—relying instead on the hemodynamic coupling between neural activity and regional changes in blood flow—they cannot be deployed as ambulatory or portable BCI systems. As a result, the majority of promising BCI systems to date exploit EEG signals.[1-9]

Raw brain data is rarely of substantial benefit, as its real value depends on data quality and on signal-processing, machine-learning, and data-mining tools to analyze the data and extract useful information. To attain high-quality brain data and, thus, a reliable BCI system, we first need to create the stimulus conditions or mental task setting that will generate maximally measurable and classifiable brain states. Next, we need to optimize the measurement procedure and develop real-time signal-processing algorithms that decode and interpret the resulting brain signals. Finally, we must integrate these features into an interface that has optimal functionality and usability.[2-6]

WHY BRAIN-COMPUTER INTERFACES?

There are several reasons why BCI is an important and active research area:

- BCI is a new neuroscience paradigm that might help us better understand how the human brain works

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in terms of plasticity and reorganization, learning, memory, attention, thinking, social interaction, motivation, interconnectivity, and much more.
- BCI research allows us to develop a new class of bioengineering control devices and robots to provide daily life assistance to handicapped and elderly people.
- Several potential applications of BCI hold promise for rehabilitation and improving performance, such as treating emotional disorders (for example, depression or anxiety), easing chronic pain, and overcoming movement disabilities due to stroke.
- BCI can expand possibilities for advanced human-computer interfaces (HCIs), making them more natural, flexible, efficient, secure, and user-friendly by enhancing the interaction between the brain, the eyes, the body, and a robot or a computer.

The interesting challenge here is to investigate real-time correlations of observable tasks or behaviors with recorded brain signals to learn how information from different sensory task and behavior streams is integrated in the brain and how researchers use this knowledge to build efficient environment-conscious devices.

Several potential BCI applications hold promise for rehabilitation and improving performance.

DREAMS VERSUS REALITY

The ideal BCI system would detect all our intentions, as well as imagined and planned actions, and even some simple thoughts at any time.[1-8] In reality, that dream remains remote for several reasons. First, we do not have sensors that are capable of detecting "intentions" or "thoughts," as our knowledge about brain signals and brain electrophysiology is still quite limited. In addition, it is extremely difficult to extract desired information from the brain's very noisy and ongoing activity, which exhibits a signal-to-noise ratio (SNR) as low as –20 dB for EEG data. To overcome this severe limitation, most signal-processing methods apply some form of averaging or spatiotemporal filtering across either repeated trials, time, or channels.[2]

Thus far, BCI researchers have proposed solutions that can discriminate a limited number of commands under strict conditions, with limited recognition accuracy, finite time to recognize and generate each command, and only during limiting activation periods (the periods of BCI system use). These constraints mean that commands must be based on well-characterized mental tasks that produce well-differentiated neuronal activity.[8]

An efficient BCI system should have the ability to

- extract relevant information correlated to specific mental tasks or events,
- adapt and self-learn in ever-changing noisy environments,
- predict user intentions (such as movement planning) swiftly and reliably, and
- take appropriate actions (control a device, give neurofeedback to a user).

To make progress in the development of more efficient and intelligent BCI/HCI systems, we must:

- record high-quality real-time brain and peripheral nervous/muscular systems data, possibly from a variety of sources and modalities—for example, EEG, fMRI, NIRS, electromyography (EMG), electrooculography (EOG), and visual-audio-touch sensors;
- transform this data into reliable information and then knowledge; and
- provide easy-to-use neurofeedback by effective visualization and sonification of the extracted brain signals as well as a graphical interface to display or visually confirm this knowledge.

A BCI system is best implemented using a modular structure, as each signal-processing block can be improved and optimized independently to achieve better performance with less effort required by the user to adjust some parameters.

BASIC SIGNAL-PROCESSING BLOCKS

As Figure 1 shows, most existing BCI systems use three basic signal-processing blocks.

The system applies a preprocessing step to remove noise and artifacts (mostly related to ocular, muscular, and cardiac activities) to enhance the SNR. In the next step, the system performs feature extraction and selection to detect the specific target patterns in brain activity that encode the user's mental tasks, detect an event-related response, or reflect the subject's motor intentions. The last step is aimed at translating—or associating—these specific features into useful control (command) signals to be sent to an external device.[2]

Preprocessing

In the preprocessing step, the system can decompose recorded brain signals into useful signal and noise subspaces using standard techniques like principal component analysis (PCA), factor analysis, singular value decomposition (SVD), independent component analysis (ICA), sparse component analysis (SCA), nonnegative matrix factorization (NMF), or nonlinear adaptive filtering.[10-17]

One promising approach to enhance signals, extract significant features, and perform some model reduction is to apply blind source separation techniques, especially multiway blind source separation and multiway array (tensor) decomposition. In fact, researchers and engi-

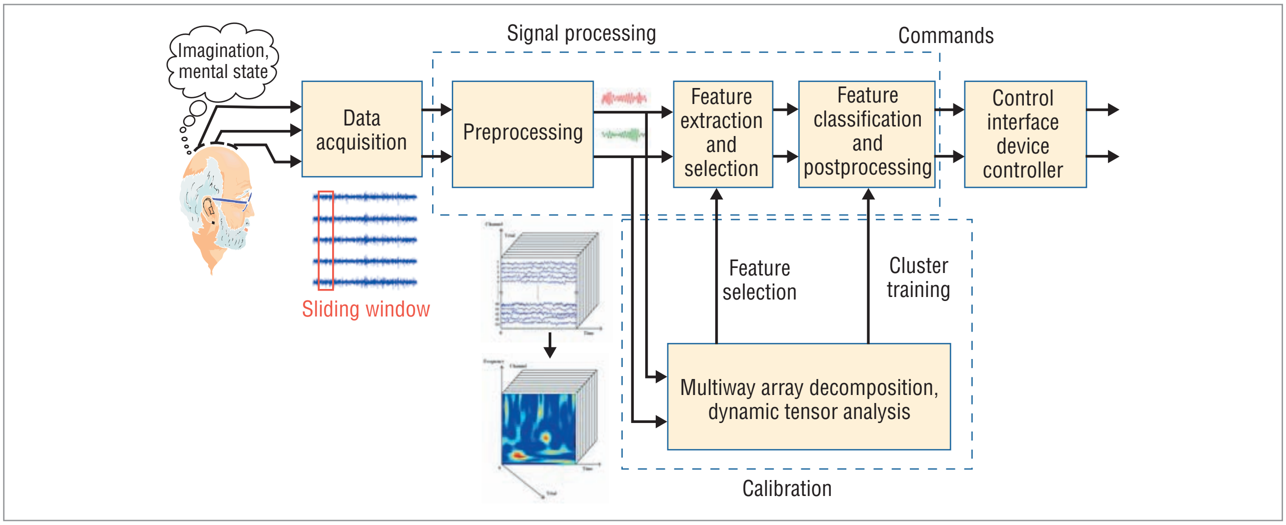

Figure 1. Multistage procedure for online BCI. Preprocessing and feature extraction play a key role in real-time, high-performance BCI systems. In the calibration step, most BCI ERP studies are based on multisubject and multicondition analysis. For such scenarios, the tensor decompositions naturally encompass extra modalities such as trials, subjects, conditions, and so on and allow the system to find the dominant sources of activity differences without supervision.

neers have successfully applied standard ICA for dividing raw data to signal subspace and noise subspace and then to extract component subsets with higher classification accuracy than using original EEG signals.[12,13] However, some physiological artifacts are difficult to filter out, especially muscle activity that is broad-banded, covers almost the whole frequency range of interest, and is not periodic. Signal-filtering efficiency is difficult to assess because it often removes as much noise as signal.[1-8]

Feature extraction

Even if filtering can remove some noise, the background brain activity remains; thus, when features are extracted, there is large variability from trial to trial, and in some cases, features are measured over many samples, increasing the signal-to-noise ratio. Features can be extracted in time, space, or frequency domains. This usually produces numerous features, which the processing module must evaluate and select to keep a reasonable training time and ease the classifier training. In fact, feature extraction is the most challenging step in BCI signal processing.

Classification

Classification methods can be distinguished as being either linear or nonlinear. The linear methods are often very simple, like thresholding or linear transformation. In nonlinear methods, neural networks and support vector machines have been applied most often.[1-9] The classifier can output several types of control signals, both discrete and continuous. Some classifiers can output a noncontrol (NC) state—for example, when the user does not think intentionally about one of the predefined tasks. Some classifiers can also output an "unknown" state if the confidence level is too low to make a decision from the observed features.

Ideally, the translator block supports the noncontrol state, because without NC support, all classifier output states are considered as intentional. With NC support, the user can control whether or not the output is considered as intentional. In the latter case, a self-paced NC state paradigm is monitored continuously, where users can perform specific mental tasks whenever they want.[1,8]

BCI PARADIGMS

There are four basic BCI-paradigm types:[1-9]

- *passive endogenous*: specific mental imagination activity—for example, motor imagery or mental arithmetic;
- *active endogenous*: active neurofeedback and unrestricted mental imagination using the operant-conditioning principle—a "no specifics" cognitive, "just do it" principle;
- *passive exogenous*: responses to externally driven stimuli to evoke specific brain responses called event-related potentials (ERPs); and
- *active exogenous*: consciously modified responses to external stimuli, often combined with neurofeedback.

One promising and popular approach based on the passive endogenous paradigm is to exploit temporal/spatial changes or spectral characteristics of the sensorimotor rhythm (SMR) oscillations, or *mu*-rhythm (8-12 Hz) and *beta* rhythm (18-25 Hz). These oscillations typically decrease during, or in preparing for, a movement—event-related desynchronization (ERD)—

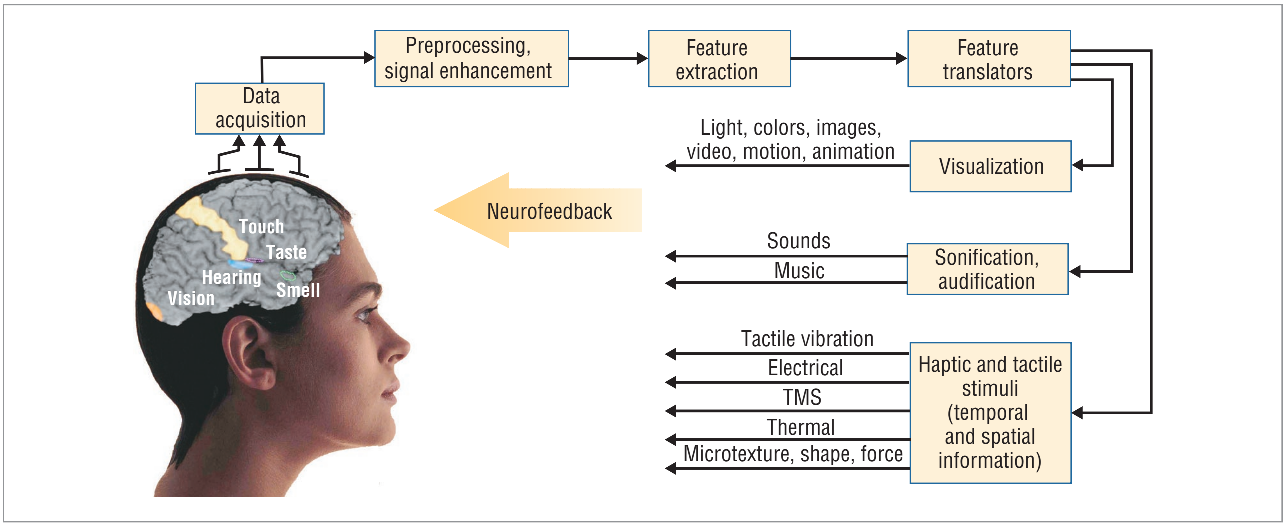

Figure 2. Conceptual BCI system with various kinds of neurofeedback combined with HCI. The development of a BCI must handle two learning systems: The computer should learn to discriminate between different complex patterns of brain activity as accurately as possible, and BCI users should learn via different neurofeedback configurations to modulate and self-regulate or control BCI activity.

and increase after movement and in relaxation—event-related synchronization (ERS).[3,4,6] ERD and ERS help to identify features associated with motor imagery EEG classification.[4-11]

In a neurofeedback-modulated response (active endogenous) paradigm, users learn to generate specific brain waves through various mental strategies while monitoring the outcome of their efforts in near real time.[7-9] Typically, the user visualizes the preprocessed and translated target brain signal to increase motivation and improve recognition accuracy. However, the user's successful control of the interface in this way usually requires quite a long process—up to several weeks of training.

BCI neurofeedback in any of these paradigms should be as speedy as possible, which requires fast real-time signal-processing algorithms. Recent neurofeedback experiments confirm that performance increases with richer feedback—for example, a simple bar gives lower accuracies than a full immersive 3D dynamic visualization or sonification.[8]

External stimuli—visual, auditory, or somatosensory—drive exogenous BCI tasks, which usually do not require special training. Two often used paradigms are P300 and steady-state visually evoked potentials (SSVEP). P300 is an event-related potential that appears approximately 300 ms after a relevant and rare event. SSVEP uses a flicker stimulus at relatively low frequency (typically, 5-45 Hz).

We have recently designed a smart multiple-choice table in the form of an array of small checkerboard images flickering with different frequencies.[13] When users focus their attention on a specific flickering image or symbol, a corresponding periodic component (SSVEP) can be observed in EEG signals (although it is buried in huge noise and is quite difficult to extract). The SSVEP paradigm remains one of the most reliable approaches for a fast BCI system that could implement a relatively high number of unique commands or symbols and support autonomous cursor navigation or a virtual joystick.[12,13]

CURRENT BCI TRENDS AND FUTURE DIRECTIONS

Current and future trends in noninvasive BCI can be briefly summarized as follows. BCI applications must evolve from

- unimodal to multimodal—that is, simultaneous monitoring of brain activity using several devices and combining BCI with multimodal HCIs;
- simple signal-processing tools to more advanced machine learning and multidimensional data mining;
- synchronous binary decision to multidegree control and asynchronous self-paced control;
- open-loop to closed-loop control—neurofeedback combined with multimodal HCI; and
- laboratory tests to practical trials in the noisy real-world environment.

The overall effectiveness of BCIs depends not only on the successful processing of the input signal, but also on the interface used to achieve a goal. From this perspective, as Figure 2 shows, there is great potential for work in the domain of the HCI to improve BCI interfaces. BCI and HCI have overlapping goals: enabling more seamless communication between human and computer. It seems that some BCI researchers tend to ignore other modalities—for example, ocular (EOG) or muscular (EMG)—because the original BCI definition states that only brain signals can be used. However, combining BCI with HCI could improve classification results. As a result, communication protocols to support the self-paced paradigms would also be improved.[8,9] Combining BCI with research in areas such as gesture recognition, gaze detection, body movement tracking, speaker recognition, human-made noise detection (for example—sigh, laugh, gasp), haptic sensors, musical interaction, facial expression, and auditory emotion analysis are quite important.

Another promising and related extension of BCI is to incorporate real-time neurofeedback capabilities to train subjects to modulate EEG brain patterns and parameters such as ERPs, ERD, SMR, and P300 to meet a specific criterion or learn self-regulation skills where users change their EEG patterns in response to feedback. Such integration of neurofeedback in BCI is an emerging technology for rehabilitation, but we believe it is also a new paradigm in neuroscience that might reveal previously unknown brain activities associated with behavior or self-regulated mental states.

A promising extension of BCI is to incorporate real-time neurofeedback capabilities to train subjects to modulate EEG brain patterns and parameters.

The possibility of automated context awareness as a new interface goes far beyond standard BCI with simple feedback control. We hope to develop the next level of BCI system using neurofeedback for some selective cognitive phenomena. To do so, we need to rely increasingly on findings from other disciplines—especially cognitive science, information technology, biomedical engineering, machine learning, and clinical rehabilitation. Although visual, auditory, tactile somatosensory, and even olfactory neurofeedback modalities are possible, visual neurofeedback has been the most frequently used method.[1-9]

Multiway array factorization and decomposition

Recent advances in developing high-spatial-density array EEG have employed multidimensional signal-processing techniques—multiway analysis, multiway-array (tensor) factorization/decomposition, dynamic tensor analysis, or Windows-based tensor analysis—to increase the performance of BCI systems.[17-26]

Standard matrix factorizations like PCA, SVD, ICA, and NMF and their variants are invaluable tools for feature selection, dimensionality reduction, noise reduction, and mining.[1-16] However, because they have only two modes or two-way representations (for example, channels and time), they have severe intrinsic limitations.

In comprehensive BCI studies, the brain data structures often contain higher-order modes such as trials, tasks, conditions, subjects, and groups in addition to the intrinsic dimensions of space, time, and frequency. In fact, specific mental tasks or stimuli are often presented repeatedly in a sequence of trials, leading to a large-volume stream of data encompassing many dimensions: channels (space), time-frequency, trials, and conditions.

For these kinds of data, two-way matrix factorizations (ICA, NMF) or "flat-world view" might be insufficient for future BCI systems. Obtaining more natural representations of the original multidimensional-data structure requires using tensor decomposition approaches so that multilinear models can retain additional dimensions or modes to produce structures that are unique and admit interpretations that are neurophysiologically meaningful.[21,22,26]

The two most promising decompositions/factorizations for N-th order tensors are the Tucker model and the more restricted PARAFAC model. Both models can be viewed as generalizations of the 2D factor/component analysis—PCA, ICA, NMF—for data with more than two modalities by imposing some additional constraints such as orthogonality, mutual independence, nonnegativity, or sparsity of hidden factors. In particular, NMF and nonnegative tensor factorization (NTF), in conjunction with sparse coding, have recently been given much attention due to easily interpretable and meaningful representation.[17-26] The advantage of the sparse NTF/NMF-based feature extraction approach is that it can yield components that are common across the space, time, or frequency domains. At the same time, it can discriminate between different conditions without prior knowledge of the frequency bands and temporal windows for a specific subject.[10,11] The "Tucker and PARAFAC Models" sidebar explains these approaches in more detail.

In general, tensor decompositions allow multichannel and multisubject, time-frequency-space sparse representation, artifact rejection in the time-frequency domain, feature extraction, multiway clustering, and coherence tracking. Our main objective is to decompose the multichannel time-varying EEG into multiple components with distinct modalities in the space, time, and frequency domains to identify components common across these different domains and to discriminate across different conditions as well.

Further operations can remove redundancy and achieve compact sparse representation. Extracted factors or hidden latent components can be grouped (clustered) together and represented collectively in a lower-dimensional space to extract features and remove redundancy, or a component can simply be pruned if it is not correlated with a specific mental task. Note that the addition of extra dimensions makes it possible to inves-

Tucker and PARAFAC Models

The Tucker model performs decomposition of N-th order tensor $\underline{\mathbf{Y}} \in \mathbb{R}^{I_1 \times I_2 \times \dots \times I_N}$ as

$$\underline{\mathbf{Y}} = \underline{\mathbf{G}} \times_1 \mathbf{U}^{(1)} \times_2 \mathbf{U}^{(2)} \dots \times_N \mathbf{U}^{(N)} + \underline{\mathbf{N}} \tag{1}$$

where $\times_N$ means an n-mode multiplication of tensor by matrix, $\underline{\mathbf{G}} \in \mathbb{R}^{J_1 \times J_2 \times \dots \times J_N}$ is a core tensor (typically, much lower dimension than tensor $\underline{\mathbf{Y}}$), $\underline{\mathbf{N}}$ is a tensor representing error or noise, and $\mathbf{U}^{(n)} = \left[\mathbf{u}_1^{(n)}, \mathbf{u}_2^{(n)}, \dots, \mathbf{u}_{J_n}^{(n)}\right] \in \mathbb{R}^{I_N \times J_N}$ is a component matrix (also called factor or loading matrix) corresponding to n-th mode (n = 1, 2 … N). The objective is to estimate online the core tensor $\underline{\mathbf{G}}$ and its dimensions and all component matrices $\mathbf{U}^{(n)}$ subject to some constraints such as sparsity and nonnegativity.

The PARAFAC model can be considered as a special case of the Tucker model in which a core tensor $\underline{\mathbf{G}}$ is reduced to a super-diagonal tensor with $J_1 = J_2 = \dots = J_N = J$ (all elements are zero except the elements on the super-diagonal, which are scaling factors). Mathematically, a standard PARAFAC model can be represented as the decomposition of a tensor as a linear combination of rank-one tensors (an N-th order rank-one tensor is a tensor that can be written as the outer product of N vectors):

$$\underline{\mathbf{Y}} \cong \sum_{j=1}^{J} \lambda_j \mathbf{u}_j^{(1)} \circ \mathbf{u}_j^{(2)} \circ \dots \circ \mathbf{u}_j^{(N)} = \underline{\Lambda} \times_1 \mathbf{U}^{(1)} \times_2 \mathbf{U}^{(2)} \dots \times_N \mathbf{U}^{(N)} \tag{2}$$

The motivation behind PARAFAC is to obtain a relatively simple decomposition such that the component matrices are determined uniquely (up to trivial permutation, sign changes, and scaling as long as several weak conditions are satisfied). Figure A provides a graphical illustration of both models.

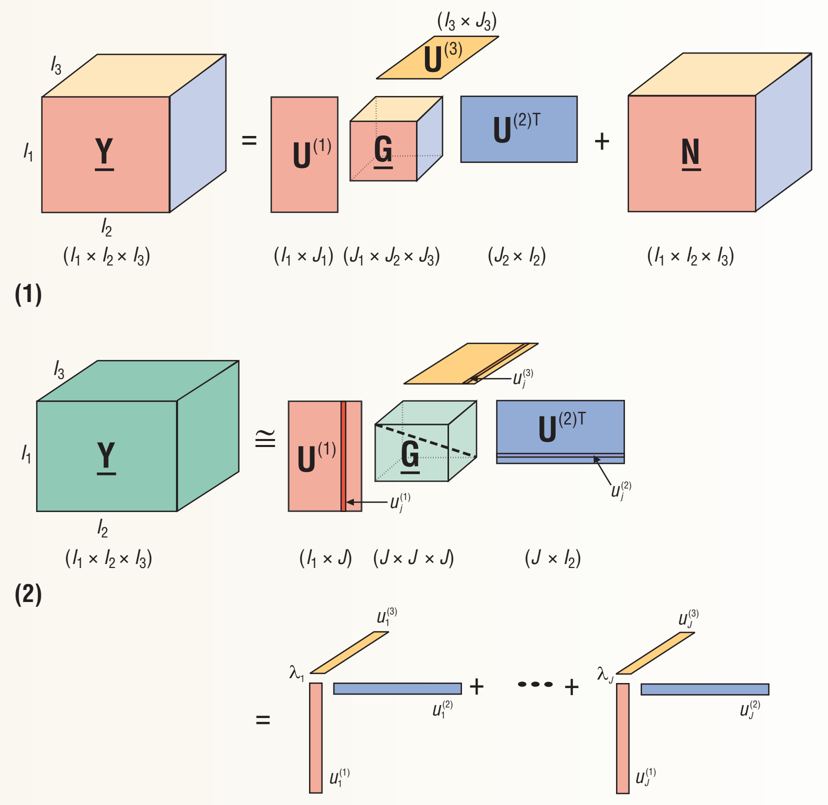

Figure A. Graphical explanation of (1) the Tucker model and (2) the standard PARAFAC model for a third-order tensor. Extracting physiological components requires imposing additional constraints such as sparseness, nonnegativity, smoothness, independence, or orthogonality.

tigate topography and time- and frequency-patterns (for example, Morlet wavelets) in one analysis.[21,26]

The resulting components can be described not only by the topography and the time-frequency signature but also by the relative contribution from the different users or conditions as shown in Figures 3 and 4. In practice, various oscillatory activities might overlap, but the sparse and nonnegative representations of the tensor

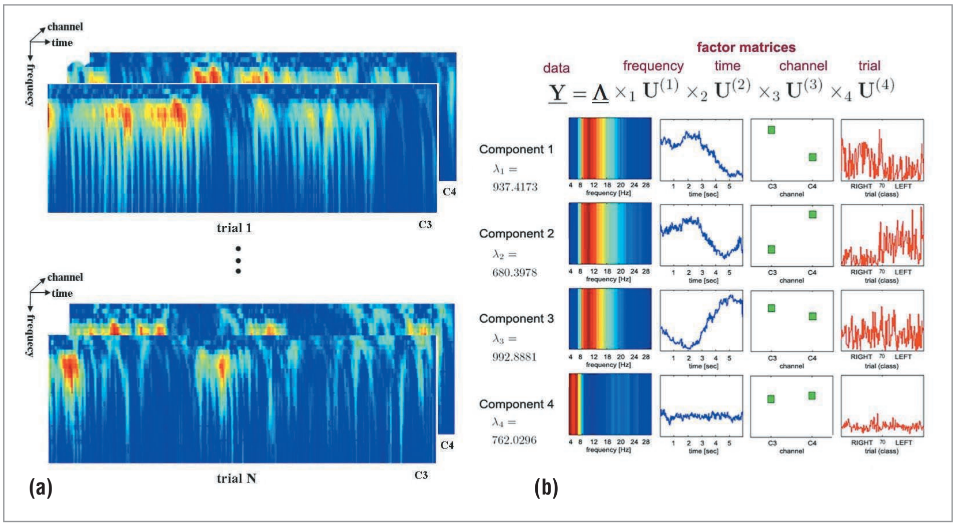

Figure 3. Four-way spectral (Morlet wavelets) EEG tensor (frequency × time × channel × trial) factorization. The example includes 140 trials recorded from the C3 and C4 electrodes during left- and right-hand motor imagery (70 trials each). (a) Each trial is represented by a 3-way tensor (frequency × time × channel). (b) The spectral tensor was factorized into four components. Component 1 corresponds to the right-hand imagery (due to the significantly greater C3 weight); component 2 represents the left-hand imagery; component 3 reflects both left- and right-hand imagery stimuli; and component 4 represents the theta rhythm (4-8 Hz), which is related to concentration.[11]

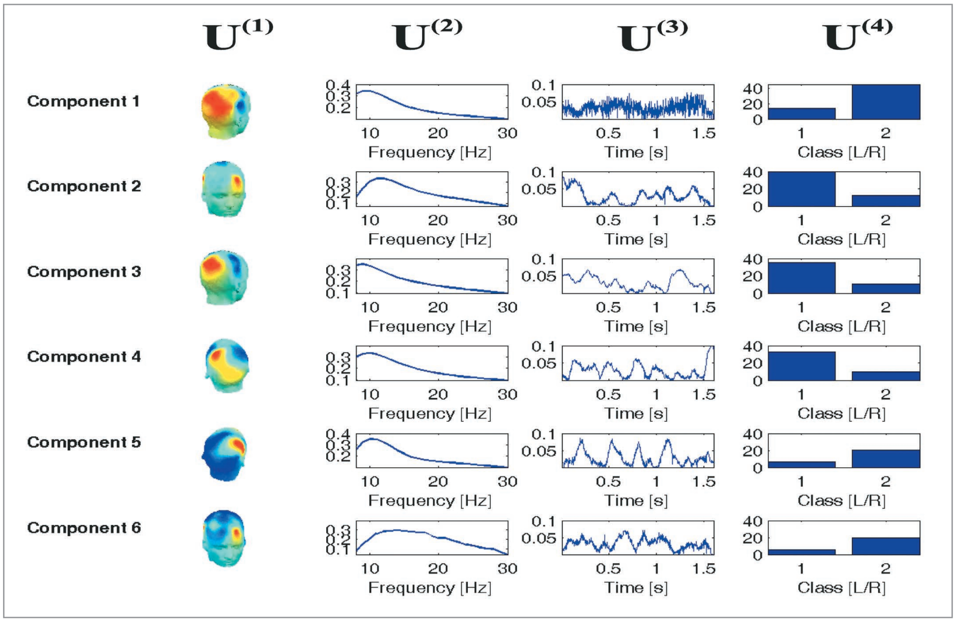

Figure 4. Experimental results using a four-way tensor decomposition of multichannel (62 electrodes) EEG data (channel × frequency × time × condition) into four factor matrices in the space (topographic map), frequency, time, and class domains shown from left to right in this figure. Finding the most discriminative components for different classes (that is, left-hand and right-hand motor imagery) requires imposing sparseness constraints on the class mode.

data given—for example, by the time-frequency-space transformation—enables the decompositions to isolate each oscillatory behavior well, even when these activities are not well separated in the space-time domain alone.

In Figure 4, components 4 and 5 correspond to imagined motor tasks from the scalp maps covering sensorimotor areas. Component 4 illustrates event-related potential phenomena (ERD/ERS) with a spatial distribution of larger amplitude on the left hemisphere and lower amplitude on the right, energy of oscillations mainly in the 8-12 Hz frequency range of *mu* rhythm, and quasi-stationary oscillations through the whole trial duration—hence the larger amplitude in class 1 and lower amplitude in class 2. Similarly, component 5 shows event-related desynchronization in the left hemisphere and event-related synchronization in the right hemisphere with lower amplitude in class 1 and higher amplitude in class 2. Components 1 and 3 show the visual evoked potentials caused by cue stimuli, which have spatial distribution on the visual cortex. Components 2 and 6 represent artifacts (ocular and muscular) and other brain activity uncorrelated to BCI.

The core of our BCI system consists of a family of fast unsupervised algorithms for tensor decompositions.[18,19,26] Thanks to their nonnegativity and sparsity constraints, NTF and NTD decompose a tensor into additive (not subtractive) factors or components. Moreover, results can be given a probabilistic interpretation.

However, we should emphasize that standard off-line algorithms for the PARAFAC or Tucker models are usually limited due to memory/space and computational constraints, and they assume static input data, while for BCI applications we are interested in multiway analysis and decomposition of dynamic streams (sequence) of tensors. In other words, brain patterns change over time, so the tensor stream should be decomposed in order to perform feature extraction and capture the structured dynamics in such collections of streams. For this purpose, we might use new concepts and algorithms for dynamic tensor analysis and Windows-based tensor analysis.[24,25] We have recently proposed new local, fast online algorithms that are promising for such models and future BCI applications.[17-19,26]

Brain-computer interfaces require accuracy, reliability, high speed, autonomous-adaptation capabilities, and flexibility (multicommand systems). To tackle the complex challenge of electrophysiological signal analysis and discrimination, we need to employ advanced signal-processing, multidimensional data mining, and machine-learning tools and their associated fast algorithms to produce an intelligent BCI platform that can accurately classify brainwaves within real-time constraints.

We believe that higher-order tensor decomposition is a promising approach for BCIs because the factors are physically meaningful (for example, scalp plots, temporal patterns, trial-to-trial variability, and so forth) and researchers can interpret them relatively easily from a neurophysiological context. We are also typically dealing with very large, high-dimensional data matrices in which we need to efficiently reduce the number of parameters for estimation, and multiway array decomposition is an efficient way to do this. Finally, tensor decompositions can impose many objectives like discrimination, multiway independence, smoothness, sparse representation, and multiway clustering.

The multiway analysis approach and related concepts (tensor decompositions, especially their extensions to dynamic tensor analysis) are only a subset of several promising and emerging signal-processing and data-mining tools with potential applications to future BCI systems. Our approach offers a flexible framework to sparsely and uniquely represent the multidimensional data stream (sequence of tensors)—that is, how to decompose multiway array data streams in the time, frequency, and space domain, and possibly under additional constraints and conditions. Since a huge volume of multiway data streaming into the BCI system needs to be monitored for feature extraction and anomaly detection in real time, developing fast algorithms for tensor decompositions and detecting patterns and correlations that might exist in coevolving data streams are crucial. We have developed our fast tensor factorization/decomposition algorithms to offer new opportunities to improve the performance of BCI systems.

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