Signal Decomposition and Noise Reduction in Single-Channel EEG: A Morphological Component Analysis (MCA) Approach

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Abstract

This study applies the Morphological Component Analysis (MCA) to single-channel EEG data obtained during human-to-human interactions in a board game (Hex-game). MCA, a dictionary-based signal decomposition method, separates signals into distinct morphological components. It enables the extraction of plausible brain activity and the removal of noise, such as ocular and muscular artifacts. By focusing on neural dynamics in interactive settings, this approach highlights the relationship between cognitive processes and social behavior. The approach suggests that MCA offers a promising framework for EEG analysis in complex, dynamic environments, combining effective feature extraction with robust artifact removal.

Keywords: EEG, Morphological Component Analysis, MCA, Signal Decomposition, Signal Denoising, Human Interaction

1. Introduction

The analysis of electroencephalogram (EEG) signals in dynamic and complex environments is inherently challenging due to the presence of noise, such as ocular and muscular artifacts, and the need to extract meaningful neural activity [1], [2]. Morphological Component Analysis (MCA) has gained attention as an effective method for addressing these challenges [3]. Utilizing a dictionary-based decomposition approach, MCA separates EEG signals into distinct morphological components, enabling the removal of noise while preserving critical neural dynamics. This dual capability makes MCA a valuable tool for applications requiring precise feature extraction, such as the study of social cognition and interactive behaviors.

This study focuses on exploring the influence of joint attention (JA) on decision-making strategies and engagement within the framework of a board game scenario (Hex-game). JA is a fundamental aspect of human social cognition, allowing individuals to align their attention with others on shared objects or activities [4]. It plays a key role in facilitating shared experiences, coordinated actions, and effective cooperation, serving as a cornerstone of human-to-human interaction [5] , [6], [7].

2. Methodology

2.1. *Experiment setup*

Hex-game is a competitive game between two players on a board of 11x11 hexagonal squares. Each player has colored hexagonal pieces in red (player A) or blue (player B). Each player alternately places a piece anywhere on an unoccupied square of the board. The first player to form a connected path of their pieces linking the opposing sides of the board marked by their color wins (Fig.1).

Eight healthy male adults (aged 21–41 years) participated in this experiment. All participants provided informed consent prior to the experiment, which was approved by the ethics committee of Kyushu Institute of Technology.

Players were fitted with a 16-electrode electroencephalographic headset and Tobii glasses. The experimental setup included simultaneous measurements with EEG, eye-tracking, and a ceiling-mounted camera, enabling the synchronized acquisition of brain activity, gaze patterns, and game progression data (Fig.2).

Players were instructed to synchronize their moves with the strong audible beat of a 50 BPM 4/4 rhythm. Each pair of players played six Hex-game matches. Each match lasted approximately 2–3 minutes. Rest periods of one minute were provided between matches to minimize fatigue(Fig.3).

EEG signals were recorded using a 16-channel system in accordance with the international 10-10 system, with a sampling rate of 512 Hz.

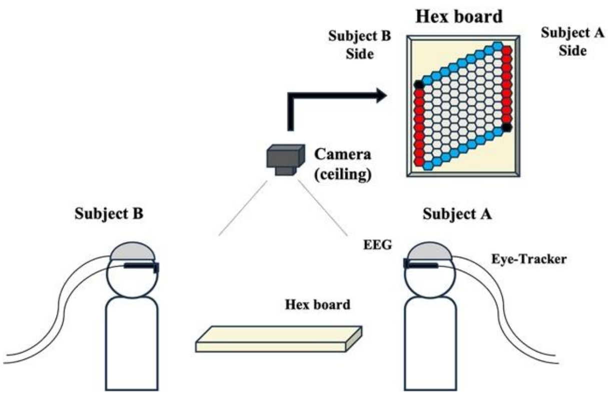

Fig.1 Hex-game Experiment Overview

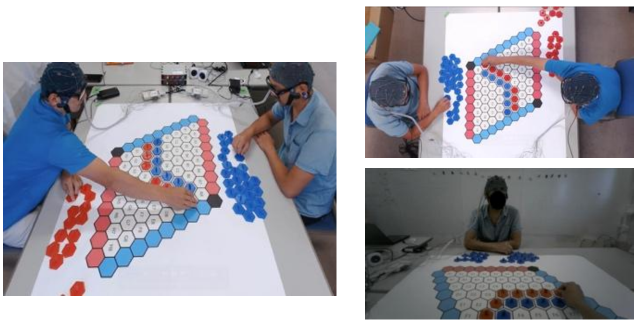

Fig.2 Hex-game experimental setup. Left: Setup overview. Top-right: Ceiling-mounted camera point of view. Bottom-right: Tobii glasses point of view.

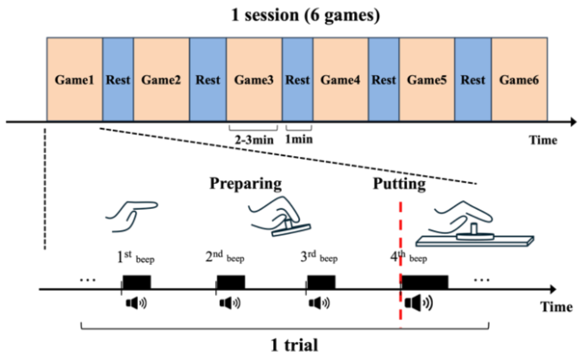

Fig.3 Timing. Top: playing and resting sequence. Bottom: Time sequence of audio instruction to place a piece

2.2. *Morphological Component Analysis*

Morphological Component Analysis (MCA) is a powerful signal decomposition technique that separates signals into distinct morphological components using principles of sparsity and redundant transforms or overcomplete dictionaries [8]. Unlike traditional methods such as Principal Component Analysis (PCA) or Independent Component Analysis (ICA), MCA is particularly well-suited for single-channel data analysis. It achieves effective noise removal while preserving the critical features of the original signal, making it an invaluable tool for applications requiring precise feature extraction and noise mitigation.

EEG signals, characterized by their specific morphological patterns—such as spikes, slow waves, and oscillatory components—are ideal candidates for MCA's sparsity-based decomposition. By employing tailored dictionaries, MCA can effectively isolate and analyze individual signal features (Fig.4):

Undecimated Wavelet Transform (UDWT): Captures smooth, low-frequency components, useful for detecting periodic activity.

Discrete Sine Transform (DST): A mathematical transformation that represents a signal in terms of sine functions. It is particularly effective in capturing spectral features with specific boundary conditions and is commonly used for signal compression and analysis in the mid-to-high frequency range.

Dirac: Identifies sharp spikes, aiding in the detection of transient events such as epileptic discharges.

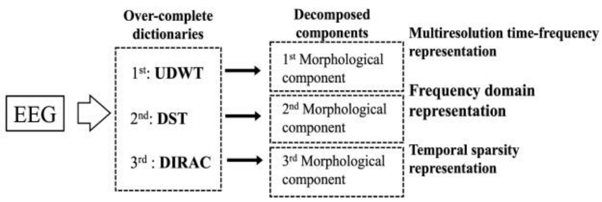

Fig.4 Overview of Morphological Component Analysis (MCA) applied to EEG signal

MCA offers several advantages for EEG analysis, 1.**Noise Resilience:** MCA effectively removes artifacts such as eye movement (EOG) and muscular activity (EMG), enhancing signal quality.
2.**Feature Extraction:** It isolates distinct morphological features, facilitating the classification of EEG states such as ictal, interictal, and non-seizure conditions.
3.**Single-Channel Capability:** Unlike ICA or PCA, MCA does not require multi-channel data, making it applicable to simpler setups.
The utility of MCA extends beyond noise removal; it enables a deeper understanding of the underlying neural dynamics by decomposing EEG signals into their constituent components. Studies have demonstrated that MCA outperforms ICA in both artifact removal and signal decomposition, particularly in single-channel scenarios. Moreover, its application in EEG signal analysis has proven effective in improving classification accuracy for machine learning models, such as Support Vector Machines (SVM), by providing well-separated, high-quality features.

2.3. *EEG data preprocessing*

Prior to processing the EEG data, a high-pass filter with a cutoff frequency of 1 Hz was applied for eliminating low-frequency noise. Then a down sampling from 512 Hz to 128 Hz has been applied to reduce the computational burden associated with EEG data analysis.

2.4. *Sliding window approach*

To ensure that transient features are effectively captured and reduce computation time, a decomposition method has been applied to individual 100-second segments with an overlap of 50 seconds.
After the splitting step, the MCA method has been applied on each 100-second segment (see 2.5) to obtain three 100-second components, one per dictionary
Finally, to preserve signal continuity and integrity, a Hann window has been applied on each 100-second component, and the Overlap-Add (OLA) method was applied to combine overlapping components for seamless signal concatenation.
The complete components extracted from each dictionary were subsequently combined to reconstruct the signal.

2.5. *MCA dictionaries*

Subsequently, MCA was applied to the 100-second segmented C3 channel data within a single game, utilizing three dictionaries (UDWT, DST, Dirac). As all participants are right-handed, C3 contains important information on cortical motor activity during the game.

2.6. *Reconstruction metric*

The reconstructed signal is the sum of the three dictionaries. Part of the original signal not corresponding to one of these three waveforms is eliminated. The Spearman's correlation between the filtered and reconstructed EEG signal is computed to evaluate the quality of the decomposition.

3. Results and Discussion

Fig.5 shows the decomposition of a filtered EEG signal in C3 during an entire session of 6 Hex-games. Ocular artifacts are mainly captured by the UDWT library. The main cortical activity is with the DST component. The Dirac component also seems to reflect artifact activity. The Spearman's correlation is high showing that all three selected dictionaries are adequate to represent the information contained in the EEG signal.
Fig.6 shows as an illustration the result of a MCA decomposition (Pair 2, Match 3, Player A, C3). In this figure, we can see that Dictionary 1 (UWDT) perfectly extracts elements correlated with player A's activity phase prior to his movement materialized by the go signal (or 4th strong beat) trigger.

Fig.7 shows that the first dictionary (UWDT) captures mainly activity in the delta band (0-4 Hz) which probably corresponds to eye movement artefact. The second dictionary (DST) shows activity in the alpha band corresponding to movement execution. And the third dictionary (Dirac) shows noise and especially the power activity at 60 Hz.

A more thorough examination of the low-frequency components (Fig.8) reveals that the second component, DST, shows notable activity in the 2-6 Hz range, potentially capturing theta waves (4-7 Hz). In contrast, delta waves (0.5-4 Hz) appear to be absorbed into the first component, mixed with slow movement-related activity. The extraction of alpha waves (8-13 Hz) and beta waves (above 13 Hz), however, remains unconfirmed at this stage [9].

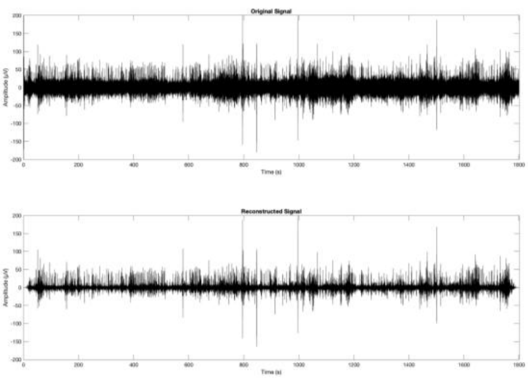

Fig.5 Comparison (corr=0.740) of original and MCA Reconstructed signals using three dictionaries (UDWT, DST, and Dirac) for an entire session of six games (Pair 2, Player A, C3).

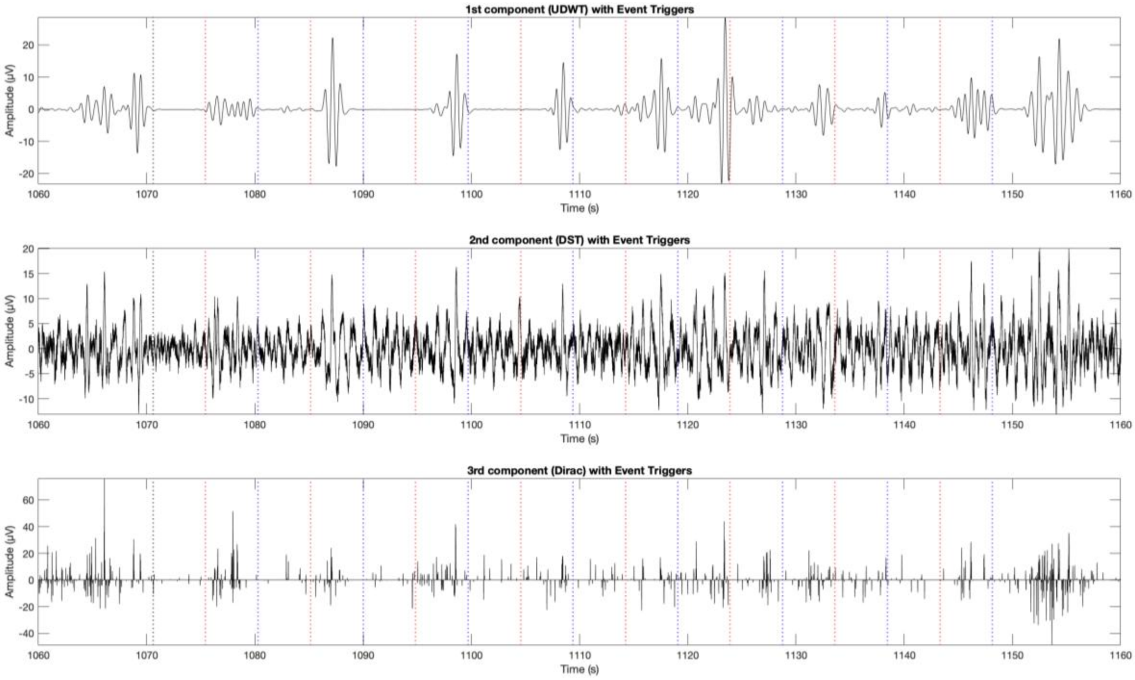

Fig.6 Results of MCA decomposition with event labels (Pair 2, Match 3, Player A, C3). Red and blue events correspond to Go signals to place a piece on board for respectively player A and player B.

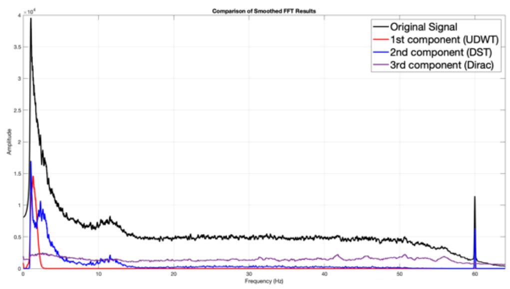

Fig.7 FFT Analysis of the smoothed original signal and components decomposed by MCA-dictionaries (UDWT, DST, and Dirac) for Pair 2/Player A-C3.

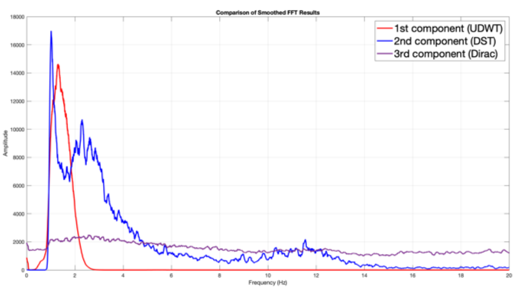

Fig.8 FFT Analysis (0-20 Hz) of the smoothed original signal and components decomposed by MCA-dictionaries (UDWT, DST, and Dirac) for Pair 2/Player A-C3.

4. Conclusion

By applying MCA to the EEG data collected during the Hex-game experiment, the method successfully isolated neural activity associated with JA while effectively removing noise artifacts, thereby enhancing signal quality. The results highlight the potential of MCA as a robust framework for EEG analysis in social and interactive contexts. This work not only deepens our understanding of social cognition in human interactions but also contributes to the advancement of adaptive communication systems in Human-Robot Interaction (HRI), particularly in dynamic and complex environments.

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