Improving Motor Imagery EEG Signal Quality with Dynamic Visual Cues: An Innovative Paradigm and Dataset

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Abstract. The electroencephalogram (EEG) acquisition paradigm is fundamental to brain-computer interface (BCI) research as it directly determines the mechanisms of brain activity evoked, significantly influencing the quality of collected EEG signals. Traditional static cueing paradigms often struggle to effectively induce the motor imagery (MI) state, which can lead to inconsistent task execution and degraded EEG signal quality. This study proposes an innovative MI data acquisition paradigm employing dynamic visual cues depicting real human movements to enhance engagement and more effectively induce the MI state. We build the first novel dynamic visual cueing MI dataset, comprising EEG data acquired using both dynamic and static paradigms from five subjects. We analyze our dynamic visual cueing paradigm using questionnaire, qualitative, and quantitative analyses, evaluating it from subjective experience, physiological phenomena, and EEG signal decoding accuracy perspectives. Experiments show that our dynamic cueing paradigm significantly enhances subjects' task understanding and concentration, leading to greater brain activation and, consequently, improved decoding accuracy of brain states in MI-BCI tasks. By eliciting more pronounced brain state activity, our method fundamentally improves the quality of acquired EEG signals, laying the foundation for accurate decoding of brain states, and provides an innovative perspective for the development and improvement of MI-BCI.

Keywords: Electroencephalogram, Motor Imagery Paradigm, Dynamic Visual Cues.

1 Introduction

The rapid advancement of brain-computer interface (BCI) technology has made electroencephalogram-based motor imagery (EEG-MI) a key research focus [1, 2]. However, the practical application of MI-BCIs still faces critical challenges, particularly in achieving stable and high-quality EEG signal acquisition, which directly affects decoding performance. One of the primary factors influencing MI signal quality is the effectiveness of visual cueing paradigms, as they play a crucial role in guiding users into an optimal MI state [3, 4]. Traditional static cueing methods, though widely used, often lack interactivity and engagement, leading to inconsistent task execution and degraded EEG signal quality [4–6]. Therefore, addressing these limitations is essential for improving MI-BCI performance and advancing brain state recognition.

In motor imagery tasks, the design of visual cues has a significant impact on the subject's motor imagery process and the modulation of EEG activity [7, 8]. Regarding the cue content, traditional cues often rely on symbolic elements not related to body parts (such as arrows or cubes) [7, 9, 10]. Although this format facilitates standardization, it has limitations in activating motor-related brain regions[11, 12]. Existing research indicates that visual cues based on body parts more directly elicit activity in motor-related brain areas compared to geometric objects. For example, observing hand movements more strongly induces central β-rhythm desynchronization than observing geometric object movements [13]. Furthermore, these types of cues can effectively activate the mirror neuron system, enhancing the subject's understanding and engagement in motor tasks by mapping visual representations to corresponding motor representations [14]. Regarding task guidance, the dynamic nature of cues is also a critical factor influencing the effectiveness of motor imagery. While static cues present fixed symbols or images lacking temporal variation which can lead to reduced engagement, dynamic cues simulate real movement processes, helping subjects enter the motor imagery state more naturally.

In this paper, we propose an innovative MI data acquisition paradigm employing dynamic visual cues depicting real human movements and present the first dataset acquired using this dynamic cueing paradigm. This paradigm utilizes dynamic image sequences of real human movements (such as hand grasping and foot opening/closing) as visual cues to naturally enhance subjects' motor imagery states. To evaluate the paradigm's effectiveness, we employ questionnaire, qualitative, and quantitative analyses, examining subjective experience, physiological phenomena, and EEG signal decoding accuracy, respectively. Questionnaire analysis captures subjects' feelings and preferences during data acquisition. Qualitative analysis, including event-related desynchronization/synchronization (ERD/ERS), time-frequency analysis, and brain topographical mapping, analyzes subjects' physiological phenomena and activation states. Quantitative analysis uses five classic, publicly available EEG signal classification models in within-session and cross-session experiments to assess the EEG signal decoding performance. Experimental results demonstrate that our proposed dynamic visual cues effectively improve subjects' attention and task comprehension and stimulate more pronounced brain states, leading to more accurate decoding.

The key contributions are threefold: (1) the introduction of a novel dynamic visual cueing paradigm for MI data acquisition, (2) the demonstration of its superior effectiveness in enhancing attention, task comprehension, and brain state decoding compared to static paradigms, and (3) the public release of paradigm and dataset facilitating further research in this area.

2 Method

The overall framework of the paper is shown in Fig. 1. This section first introduces the proposed dynamic visual cueing paradigm, followed by a detailed description of the analysis and evaluation methods used to compare it with the static paradigm.

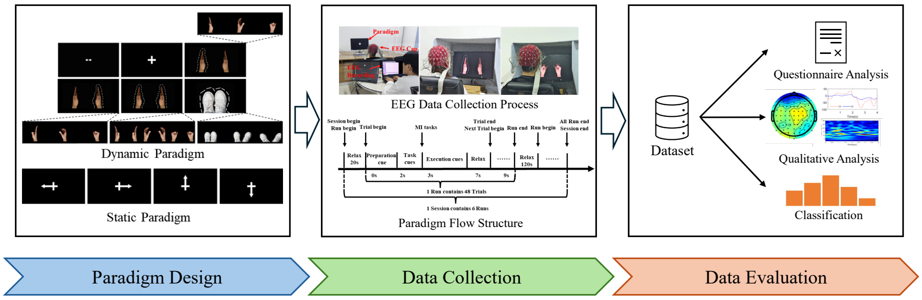

Fig. 1. Overall Framework. The Paradigm Design Part illustrates the dynamic visual cueing paradigm proposed in this paper, along with the static paradigm used for comparison. Based on these paradigms, the Data Collection Part details the acquisition of EEG data from five subjects and the construction of a dataset. The Data Evaluation Part then leverages this dataset to analyze our proposed dynamic cueing paradigm versus the static paradigm from various perspectives.

2.1 Real-Movement-Based Dynamic EEG Paradigm

To optimize the guidance effect of motor imagery tasks, we design a dynamic visual cueing paradigm based on real human movements. Through continuous dynamic visual feedback, subjects can more naturally enter and maintain the motor imagery state. The cueing procedure of this experimental paradigm is divided into multiple stages, containing three categories: preparation cues, task cues, and motor imagery execution cues. These cues are interconnected to form a complete experimental cueing procedure.

The preparation phase helps subjects adjust their state and focus before the motor imagery task. As shown in Fig. 1, an eye icon cues relaxation, while a fixation cross in the center indicates the need for increased attention. During the task cue phase, images of hands and feet will be displayed on the screen, and the category of motor imagery task to be performed in the next trial will be marked in white for 1 second. This cue is designed to help subjects quickly understand the current task before the start of each trial. Next, a motion GIF corresponding to the task is displayed for 4 seconds, depicting standardized limb movements such as hand opening and closing or alternating foot motions. These dynamic cues provide continuous visual feedback, enhancing task comprehension and engagement.

Based on the cues described above, the experimental paradigm flow structure is shown in Fig. 2, which clearly shows the complete organizational structure from Session to Run to Trial, as well as the sequence and duration of each cue stage.

At the beginning of each run, an eye icon appears for 20 seconds to cue subjects to enter a resting state. This is followed by a 2-second crosshair display with a cue sound. Next, the motor imagery task category (e.g., left hand, right hand) is shown for 1 second to clarify the task. A corresponding dynamic GIF (e.g., left hand opening and closing) is then presented for 4 seconds. The system repeats this process 48 times per run, with a 120-second rest between runs to ensure subjects adjust their state.

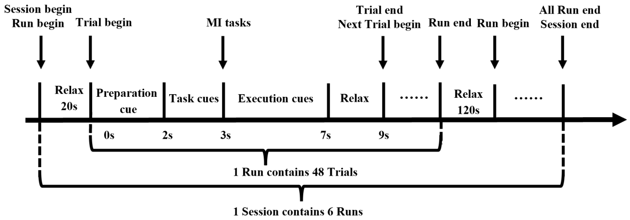

Fig 2. Experimental paradigm flow structure.

A comparative experiment is designed using a static arrow cueing paradigm based on the traditional static paradigm (shown in Fig. 1). In this version, white arrows pointing in four directions (left, right, up, and down) are displayed at the center of the screen as visual cues. Each arrow corresponds to a motor imagery task involving the left hand, right hand, both hands, or both feet, respectively. The cueing procedure for the static paradigm is consistent with that of the dynamic paradigm, with the only difference being the type of visual cue used. All other experimental procedures and parameters are kept the same.

2.2 Evaluation Methods

Questionnaire Design. In this study, the questionnaire as shown in Table 1, is designed to collect subjective feedback and preferences from subjects regarding the two experimental paradigms. It aims to gather information on the perceived differences between the paradigms, task difficulty, and levels of concentration during the experiment, providing content for subsequent data analysis.

Qualitative Analysis. To compare the effectiveness of dynamic and static paradigms in motor imagery (MI) tasks, this study examines three key aspects of brain activity: ERD/ERS phenomena, which reflects cortical excitability and motor-related neural engagement; time-frequency characteristics, which reveal dynamic changes in neural oscillations across frequency bands; and brain region activation, which identifies key motor-related cortical areas. These analyses provide a comprehensive assessment of how different cueing paradigms influence MI-related brain activity.

Quantitative Analysis. To quantitatively evaluate the effectiveness of the dynamic and static paradigms, this study tests data collected from both paradigms using five classic motor imagery EEG classification models: FBCSPNet [15], Conformer [16], EEGInception [17], EEGNet [18], and ATCNet [19]. These models represent widely used network architectures and algorithms in EEG signal processing and classification. Each model was systematically trained and evaluated to validate the reliability of the collected dataset and objectively assess whether the dynamic cueing paradigm improves motor imagery EEG signal quality and classification performance.

3 Experiments and Results

3.1 Dataset Introduction

A total of five subjects participate in the experiment, each completing multiple runs of four-class (left hand, right hand, both hands, both feet) motor imagery tasks under both dynamic and static cueing paradigms. Data are collected across two sessions, with each session containing six runs and each run consisting of 48 trials. The two sessions are separated by one week; one session involves data acquisition in the morning, and the other in the evening. EEG data are recorded using the Biosemi ActiveTwo system with 64 channels arranged according to the international 10-10 system and a sampling rate of 2048 Hz. The experimental design is approved by the ethics committee (Approval No. 202402041) and complied with the requirements of the Declaration of Helsinki. The dataset is available at https://github.com/huawen-hu/MI-EEG-DynamicCues

3.2 Questionnaire Analysis

As shown in Table 1, the questionnaire results indicate that the dynamic visual cueing paradigm significantly outperforms the static paradigm in task comprehension, concentration, and task difficulty. In terms of task comprehension, subjects find the dynamic paradigm easier to understand (average score 2.8 vs. 1.6, with lower scores indicating better understanding). Regarding concentration, subjects report better focus during the dynamic paradigm experiment (average score 4.0 vs. 2.8, with higher scores indicating better concentration). Additionally, the dynamic paradigm facilitates motor imagery more effectively (average score 3.2 vs. 1.8, with lower scores indicating easier guidance). Overall, all subjects preferred the dynamic visual cueing paradigm, citing improved task comprehension, enhanced attention, and reduced perceived task difficulty.

Table 1. Comparison of dynamic and static paradigms questionnaire results.

Evaluation metrics	Sbj1	Sbj2	Sbj3	Sbj4	Sbj5	Mean
Ease of understanding of dynamic paradigm tasks	2	1	2	1	2	1.6
Ease of understanding of static paradigm tasks	4	3	2	2	3	2.8
Concentration level in the dynamic paradigm experiment	4	3	4	5	4	4.0
Concentration level in the static paradigm experiment	3	2	2	4	3	2.8
Difficulty of motor imagery tasks in the dynamic paradigm	2	2	2	1	2	1.8
Difficulty of motor imagery tasks in the static paradigm	3	4	3	2	4	3.2
Dynamic paradigm (D) vs. static paradigm (S)	D	D	D	D	D	D

3.3 Qualitative Analysis

The Event-related Desynchronization/Synchronization (ERD/ERS) Phenomenon. Motor imagery typically elicits event-related desynchronization/synchronization (ERD/ERS) in the 8-30Hz range (the μ and β bands). We analyze ERD/ERS in this frequency band for all subjects, visualizing energy fluctuations over time in Fig. 3(a). Our method involves band-pass filtering EEG data from channels C3 and C4, squaring and averaging the results across trials, smoothing the resulting curve, and then calculating ERD/ERS percentages using the formula: ERD/ERS (%) = (X - M) / M * 100. Here, X represents the energy value at each time point, and M is the average energy during the preparation period (-1 to 0 seconds). Notably, our dynamic paradigm elicits a more pronounced contralateral activation pattern, exemplified by greater C4 activity compared to C3 during left-hand motor imagery, and vice versa during right-hand motor imagery. This enhances contralateral activation suggests improved neural engagement with the imagined movement.

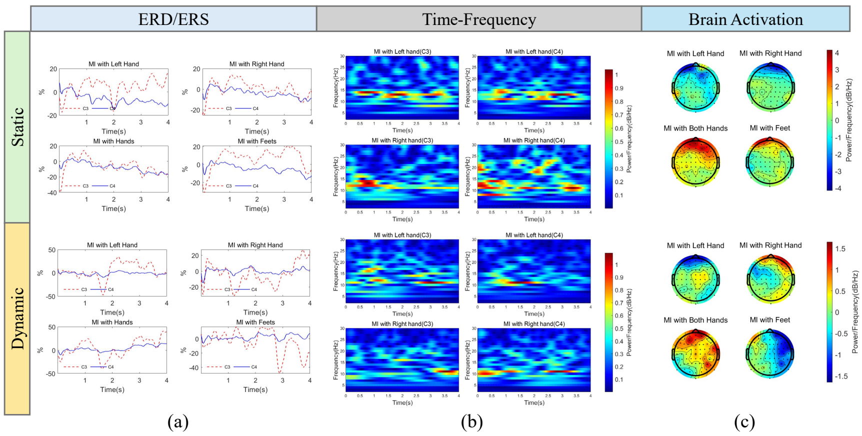

Fig. 3. Qualitative analysis results of C3 and C4 channels (Here, we present the results of Subject 2 as a representative example. Due to space constraints, results from other subjects are not shown, but they exhibit similar trends, where the dynamic paradigm demonstrates a more pronounced activation effect compared to the static paradigm).

Time-frequency Analysis. Time-frequency analysis was performed on EEG signals using wavelet transform with the complex Morlet wavelet (cmor3-3) as the basis function, leveraging its strong time-frequency localization. This decomposition into 1024 frequency bands enables fine-grained analysis of time-varying EEG components. Figure 3(b) shows the power variations in C3 and C4 electrodes (0-30Hz, 4-second window) during both motor imagery paradigms. The results indicate that our proposed paradigm elicits a more concentrated and pronounced contralateral activation pattern compared to the static paradigm.

Brain Region Activation Map Analysis. Fig. 3(c) displays the brain region activation maps for the two motor imagery task paradigms. Specifically, the 12 trials for each task are first band-pass filtered within the 8-30Hz range and averaged. Then, the topoplot function is used to generate 64-channel scalp topographies, resulting in a visualization containing four subplots. These visually represent the activation distribution across various brain regions during different motor imagery tasks and are accompanied by corresponding color bars indicating power/frequency values. Each topography represents the EEG signal power variations at different electrode locations. Examination of Fig. 3(c) reveals that our dynamic cueing paradigm induces stronger and more spatially focused activation in the sensorimotor cortex compared to the static paradigm.

3.4 Quantitative Analysis

To comprehensively evaluate the performance of the dataset, we selecte five classic EEG classification models: FBCSPNet, Conformer, EEGInception, EEGNet, and ATCNet. Two experimental schemes are designed in this study: within-session and cross-session. The within-session experiment involves dividing the data from the same session into training and testing sets. The cross-session experiment uses data from one session as the training set and data from the other session as the testing set.

Within-Session Experiment Results. The within-session experiment involves a rational partitioning of all data for each subject. The dataset is divided into training, validation, and testing sets at a ratio of 64%, 16%, and 20%, respectively.

Table 2 shows a comparison of classification accuracy between the dynamic and static cueing paradigms across five different models for subjects 1 to 5. Except for Subject 4, the dynamic paradigm data for all other subjects achieved an equal or higher average classification accuracy than the static paradigm, with most showing an improvement of over 10%. Subject 1 has the highest average classification accuracy at 85.52%, exceeding the static paradigm by 14.83%. Notably, ATCNet performs the best among the models. This indicates that the dynamic paradigm effectively enhances within-session data quality and improves the accuracy of brain state decoding.

Table 2. Within-session experiment classification accuracy (%).

Paradigm	Method	Sbj1	Sbj2	Sbj3	Sbj4	Sbj5
Static	FBCSPNet[15]	66.38	68.97	26.72	76.72	32.74
	Conformer[16]	68.1	75	36.21	82.76	41.59
	EEGInception[17]	68.1	69.83	25	83.62	42.48
	EEGNet[18]	72.41	70.69	35.34	82.76	38.94
	ATCNet[19]	78.45	76.72	39.66	87.07	39.82
	Mean	70.69	**72.24**	32.59	**82.59**	39.11
Dynamic	FBCSPNet[15]	87.07	59.48	31.03	62.93	43.1
	Conformer[16]	84.48	70.69	37.07	81.9	63.79
	EEGInception[17]	81.03	73.28	49.14	82.76	67.24
	EEGNet[18]	86.21	74.14	35.37	87.93	65.52
	ATCNet[19]	88.79	83.62	62.07	92.24	74.14
	Mean	**85.52**	**72.24**	**42.94**	81.55	**62.76**

Cross-Session Experiment Results. Compared to the within-session experiment, the cross-session experiment aims to evaluate the generalization performance of the models when processing data from different sessions, which more realistically reflects the practical value of the dataset. Cross-session data typically contains complex variations introduced by time intervals, changes in the subject's physiological state, and environmental factors, which place higher demands on the robustness of the models.

Table 3 presents the cross-session results for the dynamic and static paradigms. Except for Subject 2, whose dynamic paradigm accuracy is slightly lower than the static paradigm by only 0.15%, all other subjects shows significantly higher accuracy with the dynamic paradigm, with an average improvement of 7.96%. This suggests that the dynamic paradigm offers better cross-session consistency compared to the static paradigm, confirming its ability to elicit more stable neural responses.

Table 3. Cross-session experiment classification accuracy (%).

Paradigm	Method	Sbj1	Sbj2	Sbj3	Sbj4	Sbj5
Static	FBCSPNet[15]	52.43	51.04	28.82	58.68	29.35
	Conformer[16]	69.1	56.32	31.94	73.96	39.13
	EEGInception[17]	64.93	50.35	29.51	71.53	35.51
	EEGNet[18]	66.67	55.21	27.78	71.53	35.14
	ATCNet[19]	70.83	66.32	31.25	76.39	34.06
	Mean	64.79	**55.85**	29.86	70.42	34.64
Dynamic	FBCSPNet[15]	76.04	55.21	29.17	59.03	39.58
	Conformer[16]	71.18	53.47	31.94	70.14	44.79
	EEGInception[17]	64.93	44.1	45.49	62.85	47.22
	EEGNet[18]	67.71	56.25	31.60	77.08	50.00
	ATCNet[19]	82.64	69.44	41.67	87.5	62.15
	Mean	**72.50**	55.70	**35.97**	**71.32**	**48.75**

4 Conclusion

In this paper, we propose a novel motor imagery paradigm incorporating dynamic visual cues based on real human motion to address the limitations of traditional static cueing paradigms in EEG signal acquisition. By utilizing motion GIFs as visual cues, the dynamic paradigm aimed to naturally and effectively enhance subjects' motor imagery states and activate motor-related brain regions. Furthermore, we introduce a dynamic visual cueing motor imagery dataset.

By employing a comprehensive approach encompassing questionnaire, qualitative, and quantitative analyses, we have demonstrated the paradigm's superiority over static cueing methods. Specifically, our findings revealed significant advantages in task comprehension, attention maintenance, and perceived task difficulty, alongside more pronounced physiological phenomena such as contralateral attenuation effects. Critically, quantitative analysis showed substantial classification accuracy improvements of up to 10% across five public models. These findings indicate that the dynamic visual cueing paradigm offers superior efficiency and reliability in motor imagery tasks, making it a promising approach for future brain-computer interface applications.

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