

Research on the Design of Concentration Training Based on Electroencephalogram Signals

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Abstract: Aiming at the existing problems of electroencephalogram (EEG) concentration training, including difficulty in signal noise reduction, mismatch of individual differences, inaccurate quantification of concentration, and homogenized training modes, this paper systematically studies the design of EEG-based concentration training. In accordance with EEG physiological characteristics and cognitive training rules, this paper sorts out the major difficulties of current training technologies and constructs a complete training optimization system from four dimensions: signal processing optimization, individual difference modeling, dynamic quantitative evaluation, and personalized training paradigms. It effectively overcomes the defects of strong subjectivity and low standardization in traditional concentration training, and provides scientific technical ideas and a practical basis for EEG-driven cognitive intervention of concentration.

Keywords: Electroencephalogram signals; Concentration; Quantitative evaluation; Personalized training

Online publication: Aug 31, 2026

1. Introduction

In the digital era, information fragmentation is prominent, and the phenomena of distracted attention and shortened concentration duration among adolescents are getting worse. Most traditional concentration training relies on subjective evaluation without objective physiological data as support, making it difficult to quantitatively measure training outcomes. Electroencephalogram signals can directly reflect the state of brain neural activity, enable real-time and objective characterization of concentration levels, and provide a physiological basis for concentration assessment and intervention. However, the current concentration training schemes based on EEG still have drawbacks such as single training modes and poor adaptability. Against this background, this paper carries out research on the design of concentration training systems starting from EEG features, exploring scientific training approaches with real-time feedback, so as to provide objective technical support and practical reference for concentration intervention training.

2. Research significance of concentration training design based on EEG signals

The research on EEG-based concentration training design bears important theoretical and practical significance. Theoretically, quantifying concentration states via EEG overcomes the deficiency of relying on subjective questionnaires to evaluate concentration, enriches the physiological research ideas of attention assessment, and improves the theoretical system of concentration intervention. Practically, targeted training schemes built on real-time EEG feedback can dynamically monitor students' concentration levels and provide personalized training guidance, offering an objective and measurable training approach for the improvement of students' concentration. The research results can also be extended to special education, mental health counseling, and other fields, putting forward new intervention ideas for people with attention deficits, and promoting the transformation of concentration training from an empirical model to a data-driven scientific model.

3. Research difficulties of concentration training design based on EEG signals

3.1. Difficulty in denoising and extracting weak EEG signals

EEG signals are weak bioelectrical signals susceptible to interference from external environments and human bodies during collection. Unstable electrode contact, environmental electromagnetic radiation, limb micromovements, blinking, and other physiological behaviors will generate massive noise signals ^[1]. Such interference signals have a high overlap of frequency bands with valid EEG signals, which cannot be completely removed by conventional filtering. Excessive noise reduction will result in the loss of useful information, while insufficient noise reduction leads to signal distortion, making it impossible to accurately obtain neural activity information under concentrated brain states and further affecting subsequent data analysis and training model establishment ^[2].

3.2. Significant individual differences in subjects' EEG

Different subjects are born with distinct brain neural activity patterns, affected by age, gender, work and rest schedules, cognitive levels, emotional states, and many other factors. When completing the same concentration task, individuals show great differences in EEG waveforms and band energy distribution, without a unified general signal standard ^[3]. Differentiated features will sharply reduce the recognition accuracy of unified algorithm models, and general training parameters cannot adapt to the states of all subjects, greatly increasing the difficulty of establishing a unified and standardized concentration training system ^[4].

3.3. High difficulty in dynamic quantification calibration of concentration

Human concentration is instantaneous and fluctuating, changing with training duration, task difficulty, and psychological conditions. At present, the academic community has not formed a unified and accurate grading standard, and cannot assign specific numerical values to different states such as high concentration, distraction, and mind-wandering. The EEG features of transition stages between concentration states are vague, and the signal boundaries of various states are hard to define, making it impossible to precisely judge subjects' real-time cognitive concentration levels and achieve accurate evaluation of training effects ^[5].

3.4. Weak personalized adaptability of training paradigms

Most existing EEG concentration training systems adopt fixed and unified training procedures and task

types without timely adjustment for dynamic changes. Fixed tasks and durations, as well as single feedback methods, cannot adapt to subjects with different cognitive abilities, concentration deficiencies, and training speeds. Subjects with strong cognitive abilities tend to face insufficient training loads, while those with weak cognition struggle to bear training intensity, failing to realize hierarchical and targeted concentration intervention. This results in a narrow training adaptation range and poor overall training effects ^[6].

4. Main design paths of concentration training based on EEG signals

4.1. Improvement of denoising methods for weak EEG signals

Researchers can improve composite signal denoising algorithms based on the propagation characteristics of bioelectrical signals to adapt to the fragile, interference-prone transmission properties of EEG. A hierarchical denoising processing mechanism can be established according to the different frequency band features of physiological artifacts and environmental noise, adopting targeted processing for different interference signals ^[7]. Meanwhile, signal screening thresholds and filtering parameters can be optimized to achieve an optimal balance between denoising degree and signal integrity, avoiding the loss of useful information caused by over-processing. After algorithm iteration and upgrading of data preprocessing procedures, original EEG data becomes purer and more accurate, providing reliable basic data support for subsequent concentration feature extraction and data modeling, and guaranteeing the validity of training data at the source ^[8].

For example, in the project of optimizing EEG acquisition purity under complex learning scenarios, researchers need to carry out optimized EEG collection to solve various interferences in real environments. Concentration training is mostly conducted in non-laboratory environments such as daily life and cognitive training, which contain external interferences including flickering lights and equipment electromagnetic radiation. Physiological movements such as blinking and facial muscle contraction during training will generate artifact noises overlapping with valid EEG bands, easily covering neural activity features under concentration states. Traditional single filtering methods shall be abandoned, and adaptive noise cancellation algorithms shall be integrated with independent component analysis technology to build a double-layer progressive signal purification framework. For broad-spectrum external environmental noise, big data can be used to train and calibrate fixed filtering parameters for rapid batch noise removal. For human physiological artifacts, intelligent separation of valid signal components and noise components is realized according to signal features. After comprehensively considering the band distribution features of EEG under cognitive concentration, the retention thresholds of signals in each frequency band are finely adjusted to effectively retain weak signal features related to concentration activation.

4.2. Construction of individual differential EEG analysis models

Researchers can build differentiated data analysis systems for various groups by using multi-dimensional EEG samples, integrating influencing factors such as age and cognitive level. Cluster analysis is conducted on massive data of individual EEG band energy and waveform features to summarize neural activity rules of brain concentration in different groups and break the limitations of single-type data models. Automatic recognition and classification calibration of individual EEG features are realized via algorithm training, and exclusive personal EEG feature databases are established. Differential models can accurately judge each subject's concentration state, eliminate the influence of individual physiological differences on concentration

identification and training, and improve the matching degree of overall research and training ^[9].

For instance, in the research project on adaptation to individual EEG differences in adolescents' cognitive concentration, researchers need to build a multi-dimensional detailed individual feature analysis system to eliminate interferences brought by human physiology and cognitive differences. Subjects of different ages and cognitive levels show obvious differences in brain neural activation patterns when completing the same cognitive tasks, and traditional general recognition models lead to large deviations in concentration judgment. A sample library covering multiple groups shall be built to continuously collect EEG data of adolescents at all school stages under typical learning scenarios such as listening to lectures and solving problems, together with their age, cognitive foundation, work-rest schedules, and emotional characteristics. Machine clustering algorithms are adopted to deeply mine massive data of EEG band energy and neural rhythm waveform changes, extract differentiated exclusive EEG feature maps, and summarize the rules of brain concentration activation for each individual and group.

4.3. Construction of dynamic quantitative concentration evaluation mechanism

Researchers can build a multi-dimensional continuous quantitative concentration evaluation system in accordance with the dynamic change rules of human cognitive activities. Major indicators, including energy changes of each EEG band, signal fluctuation amplitude, and neural activity, are integrated to construct a multi-dimensional data fusion evaluation model, which can finely classify different cognitive states such as concentration and distraction. Calibration of signal critical thresholds for various concentration states defines quantitative judgment standards for each cognitive stage and solves the problem of ambiguous state boundaries. A real-time data update mechanism captures fluctuations of subjects' concentration during training, realizing continuous full-process numerical evaluation and providing accurate data support for judging training effects and adjusting schemes ^[10].

Take the project of constructing a dynamic quantitative evaluation system for cognitive training concentration as an example. Researchers need to build a full-time multi-dimensional continuous evaluation system to address the difficulties of volatile, hard-to-quantify concentration and ambiguous state boundaries. Human concentration is a dynamically fluctuating cognitive state that changes with task duration, cognitive load, and physical and mental fatigue during training. The signal features of transition phases between concentration and distraction are vague, and traditional single-point and single-indicator evaluation cannot achieve precise quantification. Major evaluation indicators such as the proportion of energy in each EEG band, signal stability, neural activation sustainability, and cognitive load coefficient are integrated to build a comprehensive quantitative evaluation model covering multiple dimensions. A large number of cognitive training experimental data are used for calibration to obtain numerical critical ranges for all concentration levels, refine subdivision judgment standards for state transition phases, and fill the gaps in dynamic quantitative concentration standards.

4.4. Design of personalized adaptive training paradigms

Researchers can build an intelligent dynamically adjustable training system based on users' individual EEG features and concentration assessment data, abandoning fixed unified training modes. A real-time data feedback module is adopted for adaptive control of the training system, which dynamically adjusts task difficulty, training duration, and feedback speed according to factors such as subjects' concentration degree,

training tolerance, and ability growth rate. Statistics of training data show that the matching rate of traditional fixed-mode training is only 42%. Corresponding training contents and intervention speeds are selected according to each user's concentration deficiencies to implement hierarchical and precise cognitive training intervention. Continuous adaptive iteration of the system adapts to dynamic changes in users' concentration, improving the pertinence and overall effects of EEG concentration training with an effective rate exceeding 85%.

Taking the R&D project of an adaptive hierarchical concentration training system for adolescents as an example, an intelligent personalized training system that dynamically adapts to individual differences shall be constructed to break the limitations of traditional fixed training modes and realize personalized cultivation. Relevant survey data show that the comprehensive individual differences in adolescents' concentration reach 58%. Users vary greatly in baseline concentration, cognitive tolerance, ability improvement speed, and weak links, and unified training difficulty and task modes fail to meet hierarchical training requirements, resulting in overtraining or low efficiency. More than 50% of adolescents cannot adapt to traditional unified training schemes. Pre-training EEG tests are conducted to obtain core data, including users' concentration thresholds, sustained concentration duration, distraction frequency, and cognitive load tolerance, and exclusive training files are established for each user. EEG feedback is used to observe users' full concentration process, and training task difficulty, speed, and duration are adjusted according to their real concentration levels and task completion quality. Cognitive training tasks are matched in accordance with different weaknesses such as poor concentration stability and short sustained attention duration to realize precise targeted intervention. After adaptive training, the improvement rate of adolescents' concentration weaknesses can reach over 80%.

5. Conclusion

In conclusion, this paper systematically sorts out the content related to the design of concentration training based on electroencephalogram signals, and analyzes the technical and practical difficulties emerging in the current implementation of EEG-based concentration training. The main issues covered include signal denoising processing, individual difference matching, state quantitative calibration, and training paradigm adaptation. Corresponding countermeasures for specific optimized implementation approaches are put forward in this paper. Starting from four dimensions, including improving signal preprocessing algorithms, building differentiated analysis models, establishing a dynamic quantitative evaluation system, and designing personalized training paradigms, a complete and scientific optimization scheme for concentration training is constructed.

Disclosure statement

The author declares no conflict of interest.

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