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Article

Biomechanical assistance for basketball training movements based on cross-domain EEG physical fitness classification

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Abstract: Cross-domain EEG signals offer valuable insights into the cortical neuron activity patterns and the functional dynamics of the central nervous system (CNS). Within the framework of biomechanics, EEG has emerged as a critical tool to investigate the interplay between neural control and physical performance. This study explores EEG complexity parameters in specific brain regions of 24 elite athletes under three distinct states: Rest, unloaded exercise, and loaded exercise. By integrating biomechanical and electrophysiological analyses, the study uncovers functional adaptations in the parietal and occipital regions, key centers for somatosensory and visual processing, respectively, in high-performance athletes. The findings reveal no significant gender differences in EEG complexity under these conditions, but highlight the effects of long-term specialized training in enhancing CNS adaptability. This adaptation is reflected in a reduced reliance on visual input, a trait distinguishing elite athletes from non-athletes. Despite the small sample size, correlations between three nonlinear EEG parameters—maximum Lyapunov exponent, approximate entropy, and Lempel-Ziv complexity—and CNS fatigue were observed. These parameters provide a robust framework for monitoring CNS fatigue and assessing the effects of exercise on neural function. This study bridges biomechanics and neural analysis, offering a novel perspective on CNS functionality under varying exercise states. The results contribute a theoretical foundation for the development of biomechanical guidance systems tailored for basketball training, with implications for optimizing athletic performance and promoting CNS health.

Keywords: cross-domain EEG; biomechanics; basketball training; nonlinear dynamics; CNS fatigue; physical performance

1. Introduction

Modern competitive sports have evolved from recreational activities into professional and specialized training systems. Prolonged high-intensity physical training imposes significant demands on the body, often resulting in physical fatigue and inhibition of central nervous system (CNS) functionality, which in turn affects overall athletic performance [1]. The mechanisms underlying CNS fatigue involve a complex interplay of neural, biochemical, and biomechanical factors [2]. This study builds on previous research in Olympic science and technology by employing advanced cross-domain EEG nonlinear dynamic analyses and ultra-slow brainwave fluctuation parameter techniques. These methods, applied during systematic, long-term training programs for Olympic athletes, aim to uncover key insights into CNS adaptations and enhance performance during high-stakes competitions. Such investigations deepen our understanding of the fundamental biomechanics and neurophysiological processes in elite athletes and contribute to more refined, evidence-based sports training methodologies [3–5].

Electroencephalography (EEG) technologies have become a cornerstone of CNS analysis, transforming complex brainwave data into interpretable visualizations through computational processing. This approach, rooted in the principles of biological cybernetics, offers a powerful tool to study the CNS's interactions with musculoskeletal and sensory systems. EEG applications span multiple domains, including biomedicine, aerospace, military medicine, and sports science [6]. However, despite decades of EEG use in sports, its potential to fully meet the nuanced demands of modern athletic training remains underexplored [7]. For example, elite shooting athletes often rely on a range of sports science technologies to enhance precision and consistency during competition. Among these, bioelectric monitoring technologies, including EEG, are increasingly recognized as critical tools for tracking athletes' physical and neural functions [8,9].

With advancements in CNS biomechanics and electrophysiological monitoring, evaluating the impact of training on neural function is now more feasible than ever. Cutting-edge algorithms and nonlinear mathematical models enable a quantitative analysis of CNS activity in elite athletes, offering novel insights into brain dynamics under training and competition conditions. This interdisciplinary approach has paved the way for the development of precise biomechanical systems for performance evaluation and optimization, bridging molecular and system-level understanding of CNS functions [10].

Previous studies have underscored the importance of cross-domain EEG analysis in understanding CNS fatigue and neuroplasticity. For instance, Huo [11] analyzed EEG characteristics of elite track-and-field athletes across various states, including rest, imagined competition, and massage-based recovery, revealing specific CNS adaptations to different stimuli. Pan [12] investigated EEG changes under high-altitude hypoxia and overtraining syndrome, highlighting significant CNS stress in elite marathon runners. These studies demonstrated that intense physical exertion imposes substantial biomechanical and neural strain, emphasizing the need for effective CNS fatigue monitoring to prevent overtraining.

Vasiljevic [13] conducted a comparative EEG study on overtrained and healthy athletes, identifying marked differences in brainwave dynamics. In healthy athletes, alpha wave amplitudes increased significantly after 15 s of high-intensity stimulation, whereas overtrained athletes showed either no change or reduced amplitudes. Moreover, during resting-state tests, overtrained athletes exhibited higher percentages of slow-wave activity, particularly in the parieto-occipital regions, which were further exacerbated after load stimulation. Similarly, Peterson [14] observed significant slow-wave frequency increases in overtrained athletes during and after hyperventilation tests, identifying this as a marker of CNS dysfunction.

Beyond traditional analyses, Kim [15] introduced bispectral EEG analysis to study nonlinear brain activity, distinguishing between resting states and active cognitive tasks such as mental arithmetic. These analyses revealed distinct nonlinear phase coherence patterns, which reflect increased neural organization during active states [16–18]. Studies of 40 Hz EEG signals have further highlighted asymmetric fractal dynamics between the left and right hemispheres during cognitive tasks, revealing a biomechanical basis for functional lateralization in the brain [19–21].

This study investigates the dynamic interplay between EEG complexity and athletic performance during specific training conditions, focusing on parieto-occipital brain regions as key centers for sensory and motor integration. Through real-time EEG data analysis of 24 athletes, findings reveal significant changes in alpha-band activity in the bilateral occipital regions during handstand training. Additionally, EEG complexity parameters varied between athletes of different skill levels and training intensities, particularly during tasks involving visual information processing. The observed reductions in EEG complexity in specific brain regions, correlated with performance outcomes, highlight the biomechanical implications of CNS function during elite training. These results emphasize the value of integrating cross-domain EEG analysis into sports biomechanics to optimize CNS fatigue management, enhance training outcomes, and refine performance strategies.

2. Construction of a sports training action assisted guidance model based on physical strength classification of cross-domain EEG

2.1. Cross-domain EEG level distribution

The bioelectric current generated during brain activity is very weak. It must undergo amplification and electromagnetic induction to convert the pulsed direct current drawn from the scalp electrodes into alternating current. After multi-stage amplification, the electrical energy is converted into mechanical energy output. Therefore, we see EEG is an indirect image of brain electrical activity. **Figure 1** shows the cross-domain EEG hierarchy topology.

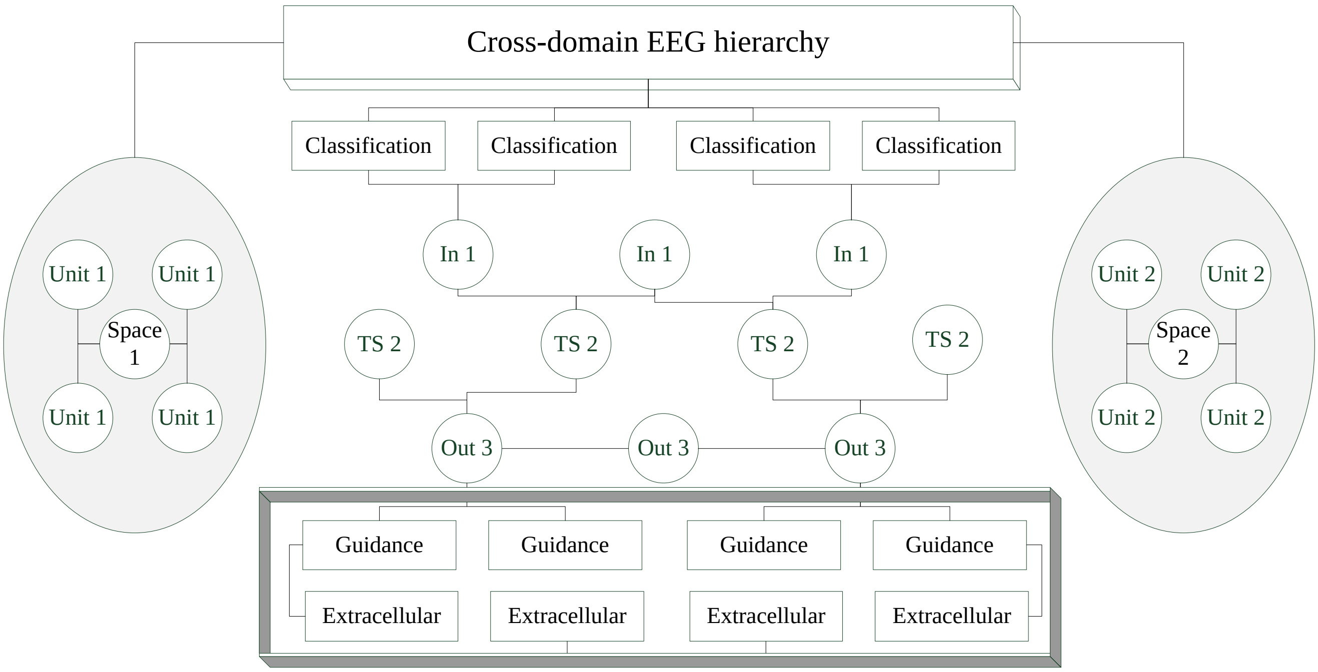

Figure 1. Cross-domain EEG hierarchy topology.

EEG activity is generated by the sum of the vertical pyramidal neuron and the postsynaptic potential of their apical dendrites. Since the dendrites of the pyramidal cells extend almost to all layers of the cerebral cortex, the currents generated by the PSPs (postsynaptic potentials) that guide the cell bodies in the deep layers of the cortex and the dendrites located on the more surface layers through the full thickness of the cortex, these neurons are tightly connected. The parallel arrangement facilitates the spatial summation of the current generated by each neuron. These neuron groups receive the same afferent impulse and hedging action and have the same direction and potential change. The sum of the currents generated by these neurons is in the extracellular space.

$$P(A,B) = P(A|B)P(B) = P(B|A)P(A) \tag{1}$$

Most of the current is confined to the cortex, and a small part passes through the meninges, cerebrospinal fluid and the skull to reach the top, causing different potential levels in different parts of the scalp. The amplitude between these potential differences is 10–1 Hv, which can be recorded between two electrodes to obtain EEG. Human EEG often contains rhythmic electrical potential changes in an awake and quiet state. These are EEG's d, e, a, and b rhythms.

$$P(S(i),S(j),\ldots,S(k)|T(t)) = P(S(i)|T(t))P(S(j),\ldots,S(k)|T(t)) \tag{2}$$

$$E(f(x)) = \sum_{i=1}^{n} w(t)^{*}f(x(t))/\sum_{i=1}^{n} w(t) \tag{3}$$

Unlike previous complexity algorithms, Lempel-Ziv complexity reflects the rate of change of new data patterns in one dimension as the length of the sequence increases. In other words, a data sequence that develops over time varies with the amount of data. Increase the rate at which the new mode changes. The performance of EEG data is complex, and its complexity reflects its degree of randomness, which determines the scale of the amount of information in this segment of the EEG data sequence.

$$|x(1) - f(x)| + |x(2) - f(x)| + \ldots + |x(n) - f(x)| = n^{*}f(x) \tag{4}$$

$$g(x) - \sum_{i,j=1}^{n} (s(1,i) + s(2,i) + \ldots + s(j,i))/s(i,j) = 0 \tag{5}$$

At the same time, it also reflects the orderly degree of information-processing activities of brain neurons. Therefore, some researchers use this algorithm to analyze EEG data. The amount of information contained in the EEG data sequence is closely related to the complexity parameter of this piece of data. For example, the higher the complexity of the EEG signal is, the higher the degree of randomness of its performance is, and the greater the amount of brain information reflected.

2.2. Fusion of physical strength classification indicators

The physical strength classification index quantitatively reflects the chaotic state of data in the phase space, making it an important metric for non-linear analysis. As the dimensionality of the data in the phase space increases, the likelihood of new patterns emerging in the time series also rises, resulting in a corresponding increase in approximate entropy. A key advantage of this indicator in non-linear analysis is that it requires relatively small datasets to calculate stable estimates, with only 100–5000 data points needed for reliable computation.

The physiological significance of brain waves lies in their frequency and amplitude characteristics. Brain wave frequencies typically range between 8–13 Hz, with amplitudes spanning from 20–100 µV. In a calm and peaceful state, brain waves are most prominently observed in the parietal, occipital, and central regions of the brain. When the eyes are closed and external stimulation is absent, their frequency remains relatively constant, and the amplitude of brain waves is symmetrical across the left and right hemispheres. While symmetry is the norm, individual variations in left-right amplitude differences do exist. The amplitude range of brain waves generally falls between 5–100 µV, with an average of 20–100 µV. These waves are easier to observe when the eyes are closed and tend to disappear quickly in response to external stimuli. For instance, when the eyes are opened, the rhythm of brain waves diminishes, indicating a strong relationship between internal suppression and brain wave activity.

Brain waves also play a significant role in the establishment of conditioned reflexes, which are closely tied to their rhythmic activity. As a result, brain wave dynamics are often used in cross-domain EEG analysis to study advanced neural activity. **Figure 2** illustrates the histogram of the intensity distribution of brain wave amplitudes. Brain waves act as a bridge between the subconscious mind and conscious thought, serving as an effective medium for accessing the subconscious. They have been shown to enhance inspiration, improve information processing, and bolster stress resilience.

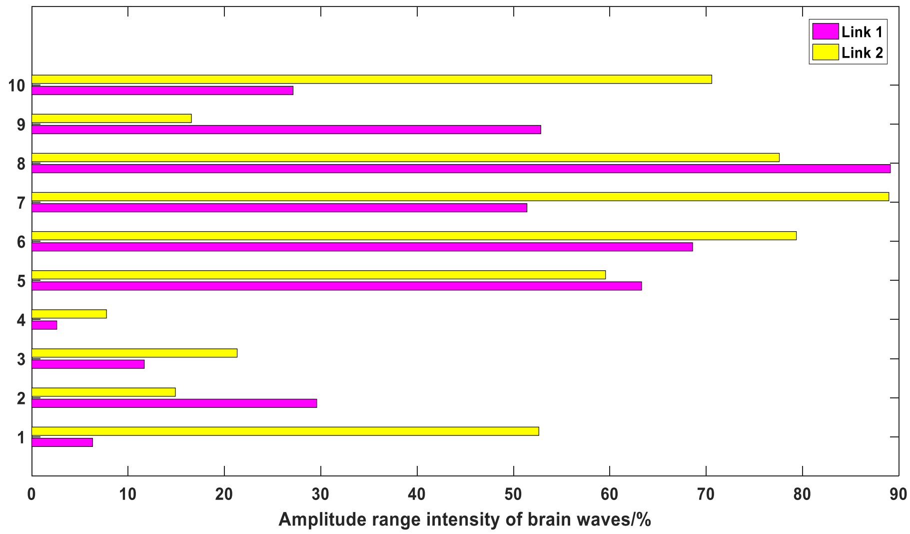

Figure 2. The histogram of the amplitude range and intensity of brain waves.

The three aspects of sports quality are related and different between reaction, movement, and displacement speeds. Therefore, the ways and methods to improve speed quality are also different. 1) Reaction speed exercises: Quick-response games can cultivate the practitioner’s ability to respond quickly to various signal stimuli; 2) Movement speed practice: The key to improving movement speed is to deal with the relationship between movement proficiency and brain excitability. Continuous repetitive exercises and perfect movement techniques can improve movement speed; 3) Displacement speed practice: The moving speed of an organism in a unit of time. The step frequency and step length determine the displacement speed. According to the movement state shown by the organism during exercise, it can be divided into reaction speed, that is, the ability to respond quickly to various external stimuli, and movement speed, that is, the length of time required to complete a single action; displacement speed, that is, the length of time to pass a certain distance in periodic motion.

2.3. Analysis of sports training factors

During physical training, the nervousness of cerebral cortex neurons decreases, and the neuronal metabolism level declines. It is due to inhibitory activities taking the initiative. The degree of inhibition depends on its initial state, that is, the activity level of the cerebral cortex before physical exercise. The higher the degree of excitement is, the deeper the degree of inhibition after sports are. The changes in the activity level of cerebral cortex neurons caused by sports are not a simple inhibitory process but to actively adjust the cerebral cortex to an appropriate degree of excitement so that the brain generates electricity. The process of orderly strengthening of activities, due to the different levels of cerebral cortex excitement in the initial state, leads to differences in the degree of inhibition of neuron electrical activity during sports. Relaxation after sports exercises can deepen the active inhibition of the cerebral cortex, and sports make the brain electrical activities. It is an alternating process of excitement-inhibition-excitement. **Figure 3** shows the index fitting of the speed quality of sports.

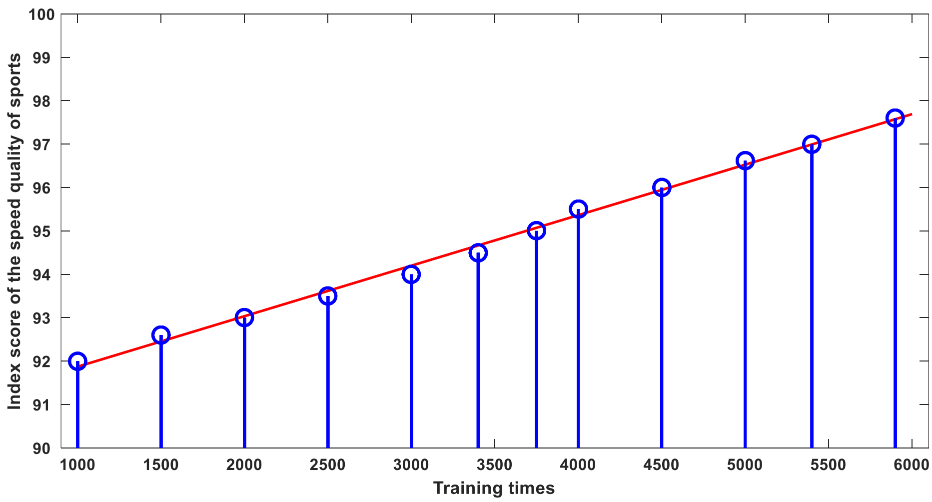

Figure 3. Fitting of index scores of sports speed quality.

Through cross-domain EEG analysis, we can observe the electrical activity of cerebral cortex neurons, which largely reflects the functional state of the central nervous system (CNS). This is crucial because the CNS plays a significant role in determining speed qualities—defined as the human body's ability to move quickly or complete an action in the shortest possible time. The functional state of the CNS, serving as the physiological foundation of speed qualities, greatly influences an individual's speed performance, especially during developmental stages. Children in these periods exhibit higher neural excitability and faster reaction times, making it a golden period for developing speed and agility.

Strength, on the other hand, refers to the muscles' ability to overcome internal and external resistance during work. It is classified in detail based on specific meanings, exercise qualities, muscle working methods, muscle contraction forms, and physical implications. Strength qualities can be divided into absolute strength, relative strength, speed strength, and strength endurance. As one of the most fundamental attributes of the human body, strength significantly affects other physical qualities such as speed and flexibility. Therefore, the level of strength is a critical indicator of an individual's training level.

2.4. Auxiliary guidance weight update

The ability of high-level athletes to concentrate their attention when performing sports appearances can be reflected by the degree of inhibition of brain electricity alpha waves. Significant differences exist in the degree of inhibition of alpha waves of athletes of different sports levels ($P < 0.001$). Athletes' stress levels to training load can be evaluated by their EEG power spectrum value. Different levels of high-level athletes have different abilities to withstand exercise load during training, and this difference is significant ($P < 0.001$). Imagery activity will increase the number of neurons involved in the activity and the brain's overall power. At the same time, it will easily lead to fatigue in the nervous center. Too much use of imagery exercises will make athletes feel anxious and nervous. Also, in the pre-match appearance tasks, the brain waves still increase in fast waves, which proves that the excitement of athletes in the pre-match state increases, or the desire to participate in the game is generated, which will inevitably produce a certain degree of tension.

Figure 4 illustrates the composition of additional guidance factors in sports performance. Among the biological factors influencing muscle strength, the following are key: The cross-sectional area of muscle fibers, muscle fiber types and motor units, the number of muscle fibers recruited during contraction, and the functional state of the nervous system. These factors, including the contractile force of muscle fibers and nervous system functionality, can be significantly enhanced through systematic training. Thus, improving both the contractility of individual muscle fibers and the functional state of the nervous system is a primary pathway for increasing overall strength. While childhood may not be the most sensitive period for strength development, targeted exercises can still effectively enhance strength quality during this phase.

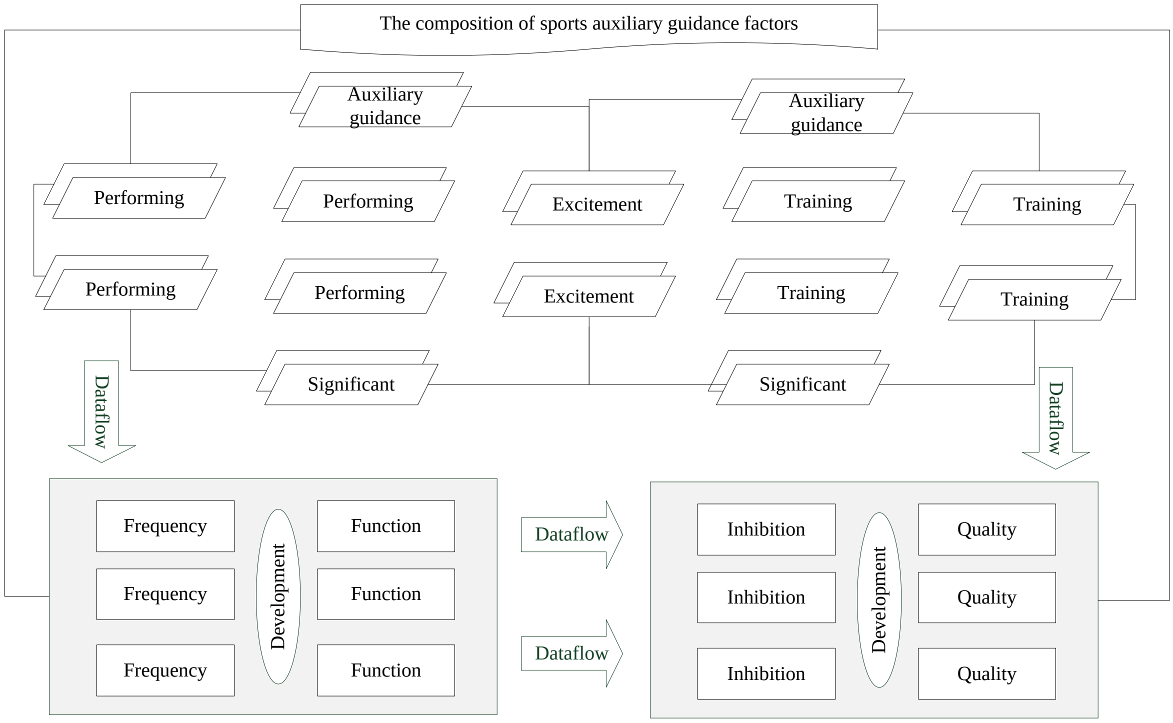

Figure 4. The composition of sports auxiliary guidance factors.

Speed quality, on the other hand, depends on several physiological foundations, including the energy supply system, muscle fibers, body structure, and the nervous system. Among these, the development and functionality of the nervous system play a pivotal role in determining speed quality. The nervous system controls muscle activity, ensuring the coordinated functioning of various muscle groups and reducing resistance caused by muscle antagonism. The frequency of alternating excitation and inhibition within the nervous system directly influences the speed of movement. Only a well-coordinated nervous system can synchronize muscle excitation and contraction frequency to achieve faster movement.

Because the nervous system is central to speed quality, improving its functionality is the most critical factor in enhancing speed performance. Childhood training is particularly effective in this regard, as it can strengthen the nervous system’s ability to alternate between states of excitation and inhibition, thereby laying a strong foundation for speed development.

3. Application and analysis of sports training action auxiliary guidance model based on cross-domain EEG physical strength classification

3.1. Cross-domain EEG data extraction

We place the dense mesh electrode cap in a 3% potassium chloride (Kc l) solution for 1 min so that the solution completely penetrates the electrode. We connect the GE lead conventional EG (Electroglottography) system to the laptop via USB. This connection Power can be obtained while transmitting data to start EEG analysis software on standby. In order to reduce the artefacts caused by various interferences, the portable computer and the conventional EEG system only use the DC (Direct Current) power supply that the portable computer is equipped with. This study selected athletes from sports colleges, 30 sports practitioners were subjects, and the experimental group members were ten blank groups, 10 A members, and 10 B members. The prescribed exercise poses were performed at a fixed practice time, and the experimental group was tested. Compared with the control group and the two control groups, there are 5 EEG physiological indicators of a peaceful state, hatha sports and B, concentration, and exercise. The power spectrum value and frequency percentage of waves one and two are statistically analyzed in each lead.

Figure 5 shows the broken line graph of the spectrum value of EEG physiological indicators. Comparing the wave rate of the athletes in the quiet and the apparent state, it can be seen that the wave rate in the apparent state is slightly higher than that in the quiet state, and the difference is significant. Imagine that after the start of the imagining exercise, from the first period to the second period, that is, the EEG power value of the imagination exercises to 1 min generally decreases, then rises and maintains at a certain level. The *P* 0.05 of each area is not statistically significant by the non-parametric related sample test K Related Samples. Sexual differences suggest that the wave activity is relatively stable during the imagining exercise, and the excitement and inhibition changes are not obvious. Among them, the difference in changes in the bilateral central area (C3, C4), bilateral parietal area (P3, P4), and bilateral occipital area are very significant ($p < 0.05$), the difference in apex (PZ) is very significant ($p < 0.01$). Compared with the untrained group, the left frontal delta wave changes significantly in group A, and the right temporal delta wave changes significantly. The delta wave changes very significantly, showing an upward trend. The right temporal delta wave has a very significant change, and the right temporal delta wave very significant change. This shows that the effect of improving delta wave B is significantly better than that of sports A. Because people only have delta waves during sleep, they will be a hundred times more energetic the next day. Therefore, if you want to improve the quality of deep sleep, you should use sports B.

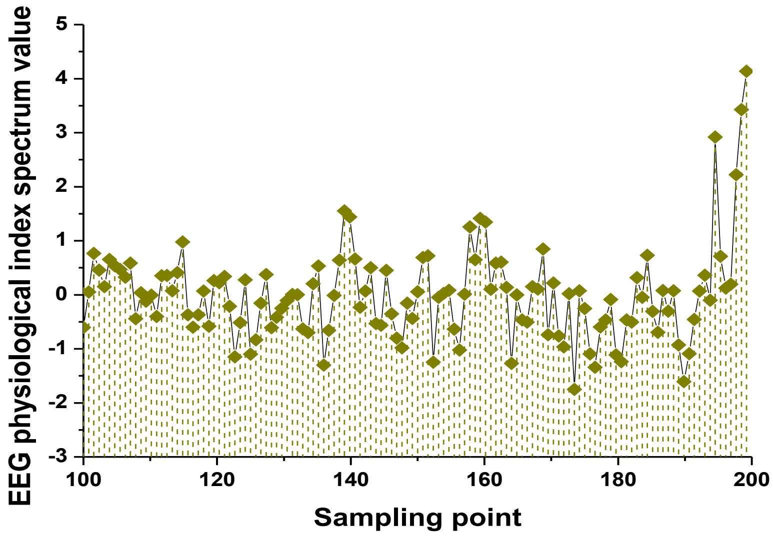

Figure 5. Line graph of spectrum values of EEG physiological indicators.

3.2. Auxiliary simulation of sports training actions

The EEG testing instrument is a portable GES (General Electric System) 120 32-lead conventional EEG system produced in the United States, which can collect EEG data in an unshielded environment. The lead Hyde dense mesh electrode cap is easy to wear, and the test electrode is positioned accurately. It conforms to the 10–20 electrode placement method recommended by the International Electroencephalography Society; the sampling recording computer is an IBM (International Business Machines) portable notebook computer based on the Windows operating system Neurotrave l (version 2.4.01) EEG analysis software. During the test, it is safe and harmless to the subjects, and it is easier for athletes to accept than certain physiological and biochemical indicators. The EEG power spectrum energy reflects the athlete's ability to adapt to the training intensity. When the EEG arousal level is between 38% and 3% and the EEG power spectrum energy is between 0.9 and 1.50, the competitive state is the best, except for the evaluation of brain function. In addition to the athlete's competitive state, it can be used as an objective indicator to evaluate sports fatigue.

Figure 6 illustrates the intensity results of the information entropy of the brain wave function. It is uncommon to use the REST-76 scale to evaluate athletes' mental and emotional states prior to a competition. However, in this study, athletes independently completed the REST-76 scale during the training period (one month before the competition) and again the day before the competition. The data were input into Excel 2013 for analysis, and a template-based evaluation was conducted. The scale consists of 76 questions covering 19 subcategories of physical and psychological evaluation, with each item scored on a scale of 0 to 6, where 6 is the maximum and 0 is the minimum. Statistical analysis of the results revealed no significant difference in the overall scores between the evaluations conducted one month prior and the day before the competition. However, an increase in social support showed a statistically significant difference, along with notable trends of overall physical condition deterioration and a decline in self-regulation ability.

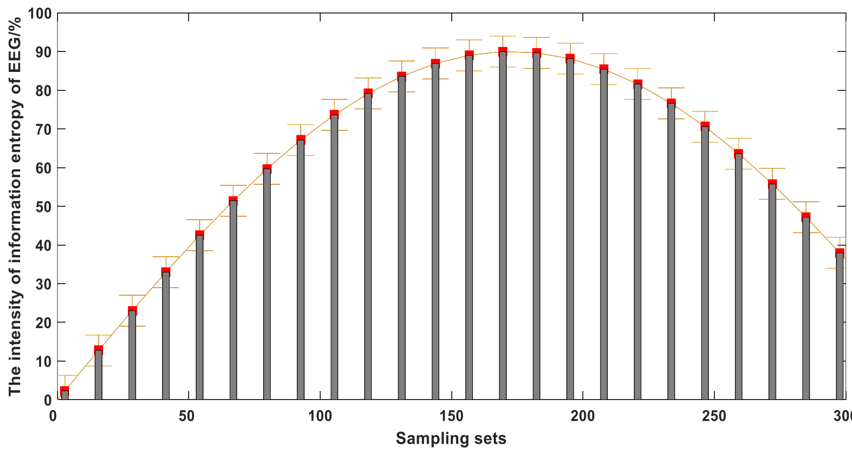

Figure 6. The intensity result of the information entropy of the brain wave function.

On the day before the competition, the balance of alpha-wave energy percentages in each brain region was observed under a resting state. Results indicated a gradual increase in the alpha-wave energy percentage from the frontal to the occipital regions. When comparing the two hemispheres, the left hemisphere exhibited a stronger energy advantage in the central, parietal, and cingulate areas, whereas the right hemisphere showed a higher energy percentage in the occipital region. In the frontal region, energy performance was similar between both hemispheres. Statistically, significant differences ($p < 0.05$) were observed in the occipital region, while no significant differences were noted in other brain areas.

3.3. Example application and analysis

The tested athlete took a sitting position, relaxed their hands, and naturally placed them on the thighs. The tester asked the athlete to close his eyes and be quiet. The test instrument traced the spontaneous EEG for 70 to 90 s, and then the tester instructed the athlete to visualize the sports movement from the start of the preparation to the end of the firing. As a signal, the tester immediately marked the segment and proceeded 34 times in a row. The evoked EEG was traced for 10 s, and the test was over. The rest-76 scale is used to measure tension and functional recovery. During the training period (1 month from the competition) and the day before the competition, the athletes fill in independently and enter the data obtained. With form software, according to the processing of the result evaluation template, out of a total of 76 questions, 19 small items of physical condition and nervousness evaluation results were obtained. The data is automatically analyzed by rest-76 processing software, and the results are obtained. **Figure 7** shows sports' function recovery scoring results based on brain waves.

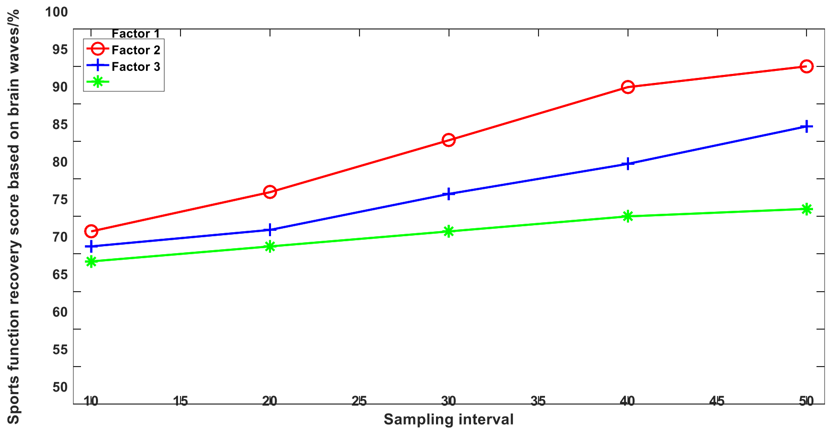

Figure 7. The function recovery scoring results of sports based on brain waves.

The results and statistically significant data are processed and statistically analyzed using the SPSS (Statistical Package for the Social Sciences) version of statistical processing software. Paired *T*-test was used for intra-group comparison, and unpaired independent sample *T*-test, correlation coefficient analysis and other statistical methods were used to compare groups. It can be seen intuitively that compared with the state of appearance before the game, the percentage of the power of the wave has been suppressed to a greater extent, from the original average value of 64.8% to 52.6%, which shows a significant difference. The ratio of low-frequency d and e waves has mostly stayed the same. The average power percentages of high-frequency B and down waves have increased from 8.2% and 8.6% at a quiet time to

9.6% and 16.8%, respectively. The power value of the right EEG after imagining exercises is reduced by 17% compared to before imagining exercises. The central area is reduced by 13%, the frontal area by 13%, and the temporal area by 37%. Non-parametric test 2 related samples have statistically significant differences suggesting the imagination exercise. The inhibition of the right frontal and right temporal areas in the right central area was significantly weakened. The parietal area was reduced by 27%, and the occipital area was reduced by 0.3%. The non-parametric test 2 showed no statistically significant difference, suggesting that after imagining exercises, the inhibition of the right parietal and occipital areas was weakened, but there was no significant change.

Figure 8 presents the fan chart of the information entropy of brain wave function. Significant changes were observed in the theta waves of different brain regions when comparing trained and untrained groups. In particular, Group A showed notable changes in left and right temporal waves compared to the untrained group. Group B, when compared to Group A, exhibited very significant changes in the right parietal waves. Additionally, while the left and right temporal wave changes remained significant between the two groups, no other differences were detected. The upward trend in theta wave results indicates that Group B demonstrates a more pronounced improvement in theta wave activity than Group A, suggesting that the interventions in Group B are more effective for enhancing theta wave activity. This enhancement facilitates achieving an optimal learning state more effectively.

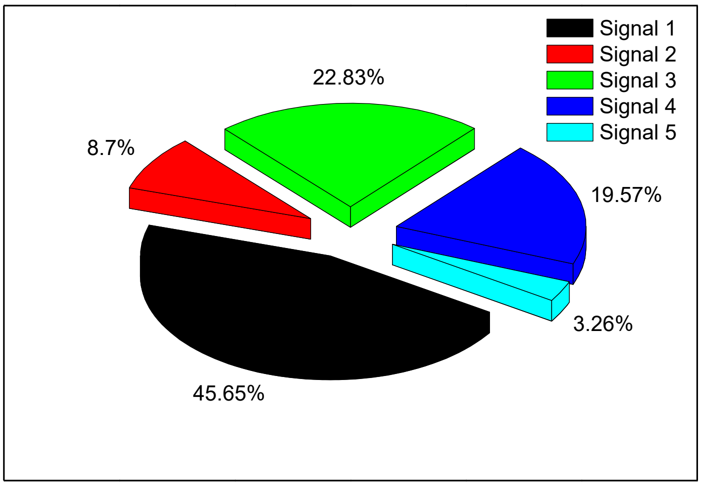

Figure 8. Fan chart of information entropy ratio of brain wave function.

Using EEG compression spectrum technology to compare brain function in high-level swimmers before and after altitude training, it was found that the main brain sequence parameters underwent significant changes during the first ten days of training at high altitudes. This period was marked by substantial increases in the level of information entropy and a noticeable trend toward greater information dispersion. These changes suggest that improper pre-competition training intensity and content can disrupt the synaptic function matrix coordination in the brain, leading to structural changes in brain function. This disruption manifests as increased information dispersion, with primary sequence parameters becoming more discrete or shifting to the right. Such shifts are associated with a decline in athletes' competitive abilities.

It is important to note that in the training of high-level athletes, traditional monitoring indicators such as physiological and biochemical markers only partially reflect athletes' functional status. These indicators often fail to accurately capture their competitive status. By incorporating advanced EEG technologies, we can gain a deeper understanding of the neural mechanisms underlying performance and develop more effective strategies to optimize training and competition preparation for elite athletes.

4. Conclusion

This study leverages EEG technology to investigate the dynamic changes in brain activity among athletes during training, providing a theoretical foundation for scientifically structuring physical education programs and optimizing sports activities. By employing modern scientific methods, this research validates the use of brainwave testing to explore the neural characteristics of athletes in different exercise states. The findings reveal patterns of cortical electrical activity during physical training and underscore the positive effects of exercise on the nervous system. These insights contribute to the development of scientific approaches for guiding athletic training and enhancing central nervous system (CNS) function. Through the analysis of three nonlinear EEG parameters—maximum Lyapunov index, approximate entropy, and Lempel-Ziv complexity—among 12 national team athletes during game preparation, this study introduces a novel method for studying advanced brain functions. The results demonstrate that regular training enhances self-regulation, alleviates anxiety and depression, and improves sleep quality, suggesting that training-induced improvements in brain function contribute to better autonomic nervous system regulation. Furthermore, these improvements help athletes overcome negative emotions, enhance psychological well-being, and strengthen their ability to handle training challenges and stress, effectively preventing CNS fatigue.

The findings also highlight that there is no significant gender difference in nonlinear EEG parameters among elite athletes. Notably, Lempel-Ziv complexity proves to be a sensitive indicator for identifying CNS fatigue in athletes, while approximate entropy reflects variations in training load and intensity during preparation phases. These nonlinear EEG parameters provide valuable tools for monitoring the functional state of the CNS, optimizing training regimens, and supporting elite athletes' mental and physical performance during intense preparation periods.

In summary, this study emphasizes the critical role of cross-domain EEG analysis in understanding brain activity under various exercise conditions. The results provide theoretical insights and practical guidance for enhancing training outcomes, improving mental and physical resilience, and preventing CNS fatigue in elite athletes.

Author contributions: Conceptualization, JT and PR; methodology, JT; software, JT; validation, JT and PR; formal analysis, JT; investigation, JT; resources, JT; data curation, JT; writing—original draft preparation, JT; writing—review and editing, JT and PR; visualization, JT; supervision, JT; project administration, JT; funding

acquisition, PR. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest: The authors declare no conflict of interest.

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