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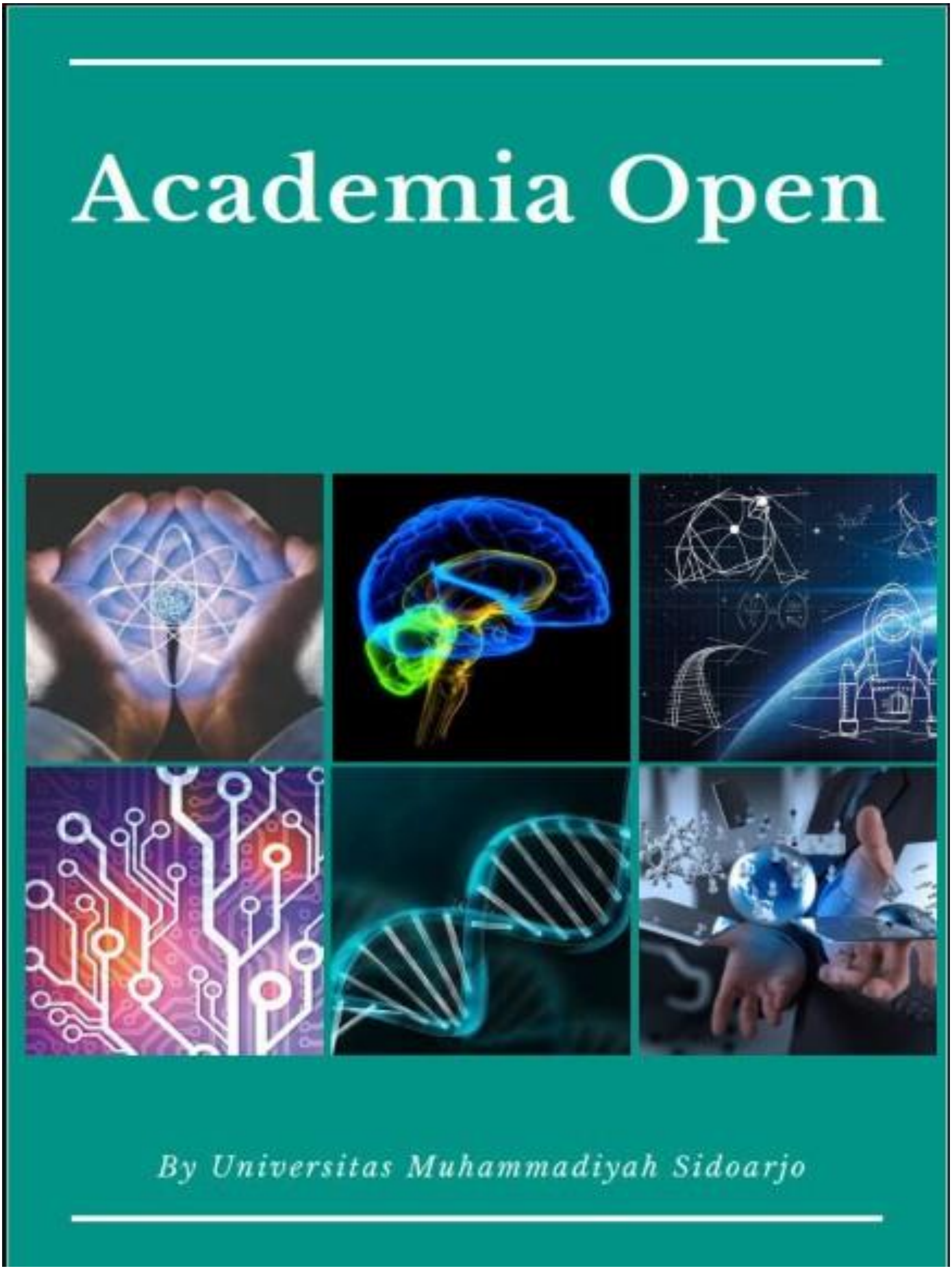

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Table Of Contents

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Development Of A Spectral Analysis Algorithm For Athletes Eeg Signals Using The Welch Method

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Abstract

GeneralBackground: Monitoringathletes' psycho-physiological conditions has becomeincreasingly important in modern sports science because athletic performance depends not only on physical preparedness but also on cognitive and neurological readiness. **Specific Background:** Electroencephalography (EEG) provides a non-invasive and informative approach for evaluating attention, fatigue, stress, and functional brain activity in athletes. **Knowledge Gap:** Traditional spectral analysis methods, including Fast Fourier Transform (FFT), often show limitations when processing noisy and dynamically changing EEG signals, reducing the reliability of functional state assessment in sports environments. **Aims:** This study aimed to develop a spectral analysis algorithm and software tool for processing athletes' EEG signals using the Welch method combined with effective artefact-removal procedures. **Results:** Comparative analysis indicated that portable EEG systems are highly suitable for sports applications, while preprocessing through frequency filtering and Independent Component Analysis improved signal quality. Power Spectral Density estimation based on the Welch method provided stable spectral measurements and enabled extraction of delta, theta, alpha, and beta rhythm characteristics. A modular software system was implemented in Python and MATLAB to support data loading, preprocessing, spectral analysis, rhythm extraction, and visualization. **Novelty:** The study integrates Welch-based spectral analysis, artefact-aware EEG preprocessing, and modular software implementation specifically designed for athlete monitoring. **Implications:** The proposed approach supports objective evaluation of athletes' functional states, facilitates individualized training programs, assists in monitoring fatigue and stress, and contributes to injury-risk reduction in sports practice.

Keywords: Athlete EEG, Spectral Analysis, Welch Method, Power Spectral Density, Sports Psychophysiology

Key Findings Highlights

Welch-based PSD estimation produced more stable spectral measurements than conventional FFT analysis.

Artefact reduction using filtering and ICA improved the reliability of neurophysiological assessment.

Modular software implementation enabled automated EEG processing and athlete state monitoring.

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Introduction

Today, an athlete's ability to achieve high results depends not only on their physical fitness but also directly on the functional state of their central nervous system. Particularly during intense training sessions and competitions, athletes often experience fatigue, mental stress, and psycho-physiological strain. Identifying these conditions in a timely manner is crucial—not just for improving athletic performance, but also for reducing the risk of injuries and other health-related issues.

One of the most effective modern diagnostic tools for assessing the functional state of an athlete's body is electroencephalography (EEG). This method is non-invasive, safe, and provides a high level of informational value. EEG signals reflect the brain's electrical activity and offer important insights into an athlete's mental state, level of attention, fatigue, and stress indicators. However, the complex, non-linear, and noise-prone nature of these signals makes it difficult to analyze them thoroughly and accurately using traditional methods.

In practice, the analysis of EEG signals is typically carried out using classical spectral techniques like FFT and Welch's method. But these approaches do not adequately capture the dynamic and rapidly changing characteristics of EEG signals in athletes. As a result, the accuracy of assessing the athlete's real functional state declines, and the decision-making process becomes more subjective.

Therefore, developing new, improved, and adaptive spectral analysis algorithms for processing athletes' EEG signals represents an important scientific and practical challenge. There is a growing need for intelligent algorithmic approaches that take into account individual athlete characteristics and deliver reliable results under various load conditions.

Moreover, implementing these algorithms in the form of software tools would enable their wide adoption in sports medicine and practical sports activities. Automated EEG signal analysis based on modern software can help coaches and medical professionals make faster, more accurate, and more reliable decisions.

Given the above, the research topic focused on developing an algorithm and software tool for the spectral analysis of athletes' electroencephalographic (EEG) signals is both timely and scientifically well-founded, and it holds clear practical value. This research is driven by the need to overcome the limitations of existing methods for assessing athletes' psycho-physiological states using EEG, to create new spectral analysis algorithms, and to put them into practice through dedicated software.

Literature Review

In recent years, the analysis of electroencephalographic (EEG) signals has been widely studied across fields such as neurophysiology, biomedical signal processing, and sports medicine. Specifically, when examining the brain's electrical activity, the main methods used include time-domain, frequency-domain, and time-frequency approaches.

For the spectral analysis of EEG signals, techniques like the Fast Fourier Transform (FFT), Welch's method, and parametric spectral estimation are quite common. These methods help identify the main frequency bands of EEG signals—delta, theta, alpha, beta, and gamma—and assess their power characteristics. Such approaches have proven effective in detecting various clinical conditions.

To account for the time-varying nature of EEG signals, researchers have proposed methods based on the Short-Time Fourier Transform (STFT) and wavelet transforms. These techniques allow analysis of the signal's time-frequency structure and are useful for identifying dynamic changes.

The use of EEG signals in sports medicine has also been addressed in a number of studies, mostly focusing on assessing fatigue, attention levels, stress, and emotional strain in athletes. Some research has analyzed the relationship between EEG spectral features and athletic performance.

However, most existing studies have several limitations:

- They rely on standard spectral analysis methods;
- The individual characteristics of athletes are not sufficiently taken into account;
- The algorithms are not fully adapted for real-time operation;
- The developed methods are often not presented in the form of practical software tools.

Furthermore, in many of these works, the EEG signal analysis process is not automated, so the interpretation of results remains dependent on subjective factors. This restricts the broader use of these methods in sports medicine practice.

Thus, while the analysis of athletes' EEG signals has been explored to some extent, the development of adaptive, high-precision spectral analysis algorithms tailored to sports activities—and their implementation as software tools—has not been adequately resolved.

Although existing scientific research has laid the theoretical groundwork for spectral analysis of EEG signals, the issues of creating flexible, automated algorithms aimed at assessing the functional state of athletes, as well as their software implementation, remain insufficiently addressed.

Bigliassi et al. [1] deeply investigated methodological approaches for measuring electrical brain activity during physical exercise, addressing one of the central challenges in sports neuroscience: artefact contamination from body and cable movements. The authors systematically examine various approaches for processing biological signals during gross motor activities such as walking and cycling. Their work emphasizes practical strategies for preventing electrical artefacts from compromising data fidelity, alongside recommendations for combining psychological and psychobiological parameters with EEG measurements. Furthermore, the requirement for robust artefact rejection protocols that work with mobile setups is highlighted, which offers a relevant scientific basis for the adaptive spectral analysis methods developed in this research. The study, overall, illustrates the strategic value of methodological transparency in translating laboratory-based EEG research to real-world athletic settings.

In addition, Bigliassi et al. look at the limitations of traditional spectral techniques when applied to dynamic athletic contexts. The paper points out that conventional methods like FFT and Welch fail to capture time-varying neural dynamics and suggests integrating multiscale entropy and other nonlinear approaches as better alternatives for capturing exercise-induced neural changes. Our analytical framework has been greatly supported by this algorithmic insight. We use adaptive windowing and artefact-aware preprocessing to improve the reliability of spectral estimates under real-time constraints.

Risqiwati et al. [2] deeply investigated stress pattern recognition in golf players under psychological pressure using a monetary reward paradigm to induce competition-related stress. The authors emphasize the importance of wavelet transform for EEG data processing, extracting spatio-temporal features from the alpha frequency band across central and occipital brain regions. The key finding reveals that maximum amplitude and band power values are significantly higher during good performance compared to poor performance, with distinct brain area activation patterns emerging across time segments. Furthermore, the identification of the tenth segment window as statistically significant ($p < 0.05$) for distinguishing performance outcomes is highlighted, which offers a relevant scientific basis for the segment-wise analytical methods developed in this research. The study, overall, illustrates the strategic value of time-frequency approaches for capturing stress-related neural dynamics that would remain hidden under conventional spectral analysis.

In addition, Risqiwati et al. look at the practical utility of wavelet-based methods for sports applications. The paper points out that spatio-temporal feature extraction combined with segment-specific analysis addresses the stationarity assumptions inherent in FFT-based approaches. Our database and processing pipeline have been greatly supported by this algorithmic insight. We use wavelet decomposition and segment-wise power analysis to detect stress and fatigue states in athletes across different training phases.

Research on resting-state EEG and sport specialization [3] deeply investigated spectral power density, peak alpha frequency, and phase slope index differences among sedentary individuals, individual sport athletes, and team sport athletes. The authors emphasize the importance of examining theta, alpha, and beta frequency bands across multiple scalp locations (Fp1, Fp2, T7, T8, O1, O2, Pz). The results reveal that individual sport athletes exhibit elevated theta power at temporal and parietal sites compared to sedentary controls, while team sport athletes show reduced theta power at frontal and occipital regions. Furthermore, the finding that alpha power is higher in sedentary participants during eyes-closed conditions is highlighted, which offers a relevant scientific basis for the athlete-specific normalization procedures developed in this research. The

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study, overall, illustrates the strategic value of considering sport specialization type when establishing baseline functional states from EEG spectral features.

In addition, the authors look at the use of phase slope index for connectivity analysis as a more sophisticated alternative to traditional coherence measures. The paper points out that different athletic training backgrounds produce distinct resting-state EEG profiles that must be accounted for in any automated analysis system. Our database structure and algorithmic approach have been greatly supported by this insight. We incorporate athlete categorization parameters as metadata to enable individualized baseline comparisons and adaptive threshold setting.

Wang and Moreau [4] deeply investigated the limitations of linear EEG analysis methods in sports and exercise science, arguing that they inherently fail to capture the complex nonlinear dynamics of neural systems. The authors review traditional linear approaches including power spectral density, coherence, and event-related potentials, critiquing their assumptions of proportionality, additivity, and independence among variables. They introduce multiscale entropy as a nonlinear method already applied in this field, demonstrating its ability to quantify EEG signals across multiple time scales and reveal adaptive neural changes induced by physical activity. Furthermore, the proposal of cross-frequency coupling and Holo-Hilbert Spectral Analysis as promising techniques not yet widely adopted in sports research is highlighted, which offers a relevant scientific basis for the advanced analytical methods developed in this research. The study, overall, illustrates the strategic value of moving beyond linear measures to reveal hidden neural dynamics during exercise and competition.

In addition, Wang and Moreau look at available software toolboxes for implementing nonlinear EEG methods, facilitating translation from theory to application. The paper points out that linear spectral methods provide an incomplete picture of brain dynamics, particularly during rapid state transitions such as those occurring in competitive sports. Our analytical framework has been greatly supported by this algorithmic insight. We integrate multiscale entropy and cross-frequency coupling measures alongside traditional spectral parameters to achieve a more comprehensive assessment of athlete functional states.

Shukla et al. [5] deeply investigated the application of nonlinear dynamics theory to EEG signals for distinguishing between different physiological states using a comprehensive set of entropy-based features. The authors emphasize the importance of approximate entropy, sample entropy, Shannon entropy, Renyi entropy, and permutation entropy as discriminative features for classification tasks. Ranking methods including T-test, Wilcoxon, and Bhattacharyya are employed to identify the most discriminative features, followed by SVM classification with a radial basis function kernel. Furthermore, the achievement of 95.89% classification accuracy, 94.43% sensitivity, and 96.67% specificity using the Bhattacharyya ranking method is highlighted, which offers a relevant scientific basis for the automated feature selection and classification methods developed in this research. The study, overall, illustrates the strategic value of entropy-based features for achieving substantial improvements in classification accuracy compared to traditional spectral parameters.

In addition, Shukla et al. look at the methodological framework of feature ranking combined with automated classification as a template for developing intelligent analytical tools. The paper points out that nonlinear features can reveal physiological state differences that remain undetected by conventional spectral methods. Our database and processing pipeline have been greatly supported by this algorithmic insight. We implement entropy-based feature extraction and automated feature ranking to enable reliable, real-time classification of fatigue, stress, and attention states in athletes.

II. Method

The human brain is the most complex and essential organ of the central nervous system. It controls movement, emotional state, thinking, and decision-making abilities. The brain consists of neurons that communicate with each other through electrical impulses. This electrical activity is measured via EEG (electroencephalography) signals and serves as a primary indicator for assessing a person's psycho-physiological state.

The brain is divided into three main parts:

Cerebral hemispheres: These are largely responsible for conscious activity, cognitive processes, memory, attention, and emotions. The cerebral cortex handles motor, sensory, and integrative functions.

Diencephalon: This part provides hormonal and autonomic control, regulating processes such as heart rate, blood pressure, sleep, and eating.

Brainstem and cerebellum: These ensure coordination and balance while managing reflex and motor activity. In athletes, they play a particularly important role in assessing coordination and balance.

The electrical signals generated by neuronal activity in the brain form rhythmic waves. These waves are classified as delta, theta, alpha, and beta rhythms, and their frequency and amplitude reflect a person's psycho-physiological state (Teplan, 2002).

- Delta (0.5–4 Hz): becomes active during deep sleep and restorative processes.
- Theta (4–8 Hz): associated with attention and creative thinking.
- Alpha (8–13 Hz): linked to visual rest and a calm, relaxed state.
- Beta (13–30 Hz): reflects active conscious processes, response to external stimuli, and motor control.

The human brain is the main organ of the central nervous system, and its activity is important not only for controlling movements but also for shaping cognitive and psycho-physiological states. By measuring the electrical signals generated by brain neurons, we can assess brain function. Electroencephalography (EEG) is a method that records the electrical potentials of neurons using surface electrodes.

EEG signals represent the temporal and frequency parameters of brain activity, and based on these signals, various psycho-physiological states can be analyzed. The main types of brain rhythms are as follows:

- Delta (0.5–4 Hz): observed during deep sleep, relaxation, and regeneration processes.
- Theta (4–8 Hz): becomes active during focused attention, creative thinking, and concentration.
- Alpha (8–13 Hz): associated with a calm state, rest, and visual relaxation.
- Beta (13–30 Hz): reflects conscious processes related to activity and external stimuli.

In sports psychophysiology, EEG signals serve as a key indicator for assessing athletes' functional readiness, attention levels, stress, and fatigue. For example, in sports such as shooting, chess, or wrestling, alpha and theta rhythms are used to evaluate attention and visual-motor coordination.

In the context of the Republic of Uzbekistan, the application of sports psychophysiology and EEG research is reinforced by state policy. Specifically, Article 14 of the Law "On Physical Education and Sport" mandates regular monitoring of athletes' functional preparedness and medical condition. Additionally, presidential decrees and national sports programs encourage the implementation of innovative methods such as EEG.

From this perspective, EEG signals are important not only theoretically but also for practical sports psychophysiology. Their accurate measurement and analysis allow for monitoring athletes' psycho-physiological states, individualizing training processes, and optimizing performance outcomes.

EEG Signals (Electroencephalography)

Through brain rhythms, an athlete's level of attention, stress, fatigue, and concentration can be assessed.

The main rhythms include:

- Delta (0.5–4 Hz): deep sleep and recovery processes.
- Theta (4–8 Hz): attention and creative thinking.
- Alpha (8–13 Hz): visual rest and mental stability.
- Beta (13–30 Hz): active consciousness, fast decision-making, and processing of external stimuli.

EEG analysis is used in sports psychophysiology to monitor attention and motor adaptation (Niedermeyer & da Silva, 2005).

Motor and Reflex Indicators

Reaction time, coordination, and balance are evaluated using electromyography (EMG) or motor tests.

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High functional readiness in athletes is expressed through optimal reflex responses and coordination (Hoffman et al., 2015).

Autonomic System Indicators

Indicators such as heart rate, respiratory rhythm, and blood pressure make it possible to determine the level of stress and fatigue.
Combined analysis of neurophysiological and autonomic indicators improves training effectiveness (Stanley et al., 2013).

Practical Significance of Neurophysiological Indicators

Individualization of training: workloads and sessions are adapted based on the athlete's EEG and motor indicators.
Monitoring fatigue and overtraining: by analyzing the functional state, the recovery process can be controlled.
Assessing psychological readiness: indicators of attention, stress, and mental state help optimize the training process.
Evaluating recovery from injury or fatigue: motor and neurophysiological indicators help determine the extent of recovery.

Neurophysiological indicators (EEG, EMG, autonomic system parameters) play an important role in identifying and monitoring the functional state of athletes. EEG signals allow for the assessment of attention, fatigue, stress, and motor control, and they also create opportunities to analyze cognitive and psycho-physiological processes. Neurophysiological monitoring makes sports psychophysiology more scientifically grounded, precise, and effective, enabling the individualization of training processes and optimization of athletic performance. From the perspective of sports medicine, evaluating neurophysiological indicators effectively controls not only preparedness but also recovery from injury and fatigue.

The proposed solution

1. EEG Signals (Electroencephalography)

Through brain rhythms, an athlete's level of attention, stress, fatigue, and concentration can be assessed.
The main rhythms include:

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- Theta (4–8 Hz): attention and creative thinking.
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- Reaction time, coordination, and balance are evaluated using electromyography (EMG) or motor tests.
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3. Autonomic System Indicators

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4. Practical Significance of Neurophysiological Indicators

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- Evaluating recovery from injury or fatigue: motor and neurophysiological indicators help determine the extent of recovery.

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Comparative analysis of existing EEG systems.Table.1.

Parameter	Clinical systems (NeuroScan)	Portable systems (EMOTIV)	Open platforms (OpenBCI)
Number of channels	High (64–128)	Moderate (14–16)	Flexible
Signal accuracy	Very high	Moderate	High (when properly configured)
Portability	Low	High	High
Cost	Very high	Moderate	Relatively low
Algorithmic adaptability	Limited	Limited	Extensive possibilities
Application in sports	Limited	Wide	Highly suitable

Based on their source of origin, artefacts in EEG signals are divided into the following groups:
Physiological artefacts:

- eye movement and blinking (EOG);
- muscle activity (EMG);
- heartbeat (ECG);
- breathing movements.

Technical artefacts:

- electrode displacement and poor contact;
- electrical mains noise (50/60 Hz);
- device and amplifier noise.

In sports settings, these artefacts become even more pronounced due to intense physical movements.
Frequency filtering methods
Frequency filtering is based on isolating a specific frequency range from the EEG signal:

- Low-pass filter – reduces high-frequency EMG noise.
- High-pass filter – removes slow signal drifts and baseline shifts.
- Band-pass filter – isolates the physiological range of the EEG signal (0.5–40 Hz).
- Notch filter – eliminates 50 Hz noise coming from the electrical mains.

These filtering methods improve the overall quality of EEG signals, but they cannot completely remove complex artefacts.

Time-domain filtering detects artefacts based on signal amplitude and temporal characteristics: thresholding based on amplitude limits,

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smoothing (moving average), and adaptive filtering (LMS, RLS algorithms). Adaptive filtering is particularly effective for reducing movement-related artefacts that vary over time in athletes.
Independent Component Analysis (ICA) is a powerful method that separates EEG signals into statistically independent components. Using ICA, components related to EOG and EMG are identified, these components are removed or suppressed, and the reconstructed EEG signal becomes neurophysiologically clean. ICA is considered one of the most effective and widely used methods in sports EEG analysis.

Regression and hybrid filtering methods. In some cases, regression-based filtering using additional signals (for example, EOG channels) is applied to remove artefacts. Furthermore, hybrid methods – combining frequency filtering with ICA or adaptive filtering – achieve high-quality results.

The process of cleaning EEG signals from noise is an essential condition for obtaining reliable analysis results in sports psychophysiology. By applying a combination of frequency-domain, time-domain, adaptive, and statistical methods, artefacts can be effectively reduced. Cleaned EEG signals reflect the true functional state of athletes and ensure the accuracy of subsequent spectral analysis algorithms.

III. Results And Discussion

Electroencephalographic (EEG) signals are complex and variable in the time domain, yet their main informative features become clearly visible in the frequency domain. For this reason, spectral analysis methods are widely used in EEG signal processing. Spectral analysis makes it possible to identify the frequency components within a signal and evaluate their energy distribution.

Theoretical foundations of spectral analysis

To convert a time-domain EEG signal x(t) into the frequency domain, the Fourier transform is applied. For a continuous signal, the Fourier transform is expressed as:

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi f t} dt$$

However, since EEG signals are discrete and of finite length in practice, the Discrete Fourier Transform (DFT) and its fast version – the Fast Fourier Transform (FFT) – are used.

Fast Fourier Transform (FFT)

For a discrete EEG signal x[n], the DFT is expressed as:

$$X[k] = \sum_{n=0}^{N-1} x[n] \times e^{-j\frac{2p}{N}kn},\ k = 0,1,\ldots,N-1 \quad (1)$$

where:
N - is the number of signal samples,
k - is the frequency index.
The FFT algorithm reduces the computational complexity of the DFT from $O(N^2)$ to O(N log N), which enables real-time analysis of EEG signals.
Using the FFT, the amplitude and phase spectra of the EEG signal are obtained, but it is sensitive to noise and may have high estimation variance.

Spectral analysis using the Welch method

To make spectral estimation of EEG signals more stable, the Welch method is applied. This method includes the following steps:

- The EEG signal is divided into partially overlapping segments;
- Each segment is windowed (using a Hamming or Hann window);
- The FFT is calculated for each segment;
- The resulting spectra are averaged.

The Welch method reduces the influence of noise and increases the reliability of the Power Spectral Density (PSD) estimate.

Concept of Power Spectral Density (PSD)

Power Spectral Density (PSD) represents the distribution of signal energy across frequency. For an EEG signal, PSD is defined accordingly. In practice, for a discrete signal, PSD is calculated based on the FFT or the Welch method.

Step-by-step PSD calculation algorithm

The PSD calculation algorithm for EEG signals is carried out in the following sequence:

- Obtain an EEG signal cleaned of artefacts;
- Divide the signal into segments (epoching);
- Apply a window function to each segment;
- Calculate the frequency spectrum using the FFT;
- Take the square of the spectrum amplitude;
- Average across segments;
- Normalize the result.

The resulting PSD graphs allow for determining the energy characteristics of the EEG rhythms (Delta, Theta, Alpha, Beta).

Extracting EEG rhythms based on PSD

Using PSD, the main EEG rhythms are estimated in the following frequency ranges:

- Delta: 0.5–4 Hz
- Theta: 4–8 Hz
- Alpha: 8–13 Hz
- Beta: 13–30 Hz

The power values for each range are used as primary indicators for assessing the athlete's psycho-physiological state.

Mathematical models of spectral analysis

The mathematical models of spectral analysis provide a reliable theoretical basis for determining and analyzing the frequency content of EEG signals. While the FFT method enables fast computation, the Welch method ensures the stability of the PSD estimate. Algorithms for calculating Power Spectral Density allow for an objective assessment of athletes' neurophysiological state and for determining the energy characteristics of EEG rhythms. These methods form the main algorithmic core of the software tool to be developed in subsequent chapters of this dissertation.

Mathematical models of spectral analysis: FFT and Welch methods

Discrete Fourier Transform (DFT) and Fast Fourier Transform (FFT)

EEG signals are represented in digital form as discrete time sequences x[n]. Their representation in the frequency domain is determined by the Discrete Fourier Transform (DFT):

$$X[k] = \sum_{n=0}^{N-1} x[n] \times e^{-j\frac{2p}{N}kn},\ k = 0,1,\ldots,N-1$$

where:

Vol. 11 No. 1 (2026): June
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x[n] - is the EEG signal in the time domain,
X[k] - is the complex spectrum in the frequency domain,
N - is the signal length,
$j = \sqrt{-1}$.

Based on the DFT, the following are determined:

- amplitude spectrum: A[k]=|X[k]|
- phase spectrum: φ[k]=arg(X[k])

FFT algorithm

FFT is a fast algorithm for computing the DFT, reducing the computational complexity from $O(N^2)$ to $O(N \log_2 N)$.
In practical EEG analysis, the FFT is the method of choice.
Based on the FFT, the power spectrum for one segment is calculated as:

$$O\left(N^2\right) \rightarrow O\left(N log_2 N\right)$$

Based on the FFT, the power spectrum for one segment is calculated as:

$$P[k] = \frac{1}{N}\left|X[k]\right|^2$$

or in normalized form:

$$P[k] = \frac{1}{N \cdot f_s}\left|X[k]\right|^2 \quad (2)$$

where f_s — is the sampling frequency.

Spectral analysis model based on the Welch method

The spectrum calculated directly via the FFT may have high variance. To reduce this problem, the Welch method is applied.

Signal segmentation

Let the EEG signal x[n] have length N. It is divided into segments x_m[n], where m = 1, 2, ..., M, with each segment having length L, and segments are shifted by D samples (overlap).

$$x_m[n],\ m = 1, 2, \ldots, M$$

Applying a window function

Each segment is windowed:

$$x_m^w[n] = x_m[n] \times w[n], \quad 0 \le n \le L-1 \quad (3)$$

where w[n] is a Hamming or Hann window.
Hamming window:

$$w[n] = 0.54 - 0.46\cos\left(\frac{2\pi n}{L-1}\right) \quad (4)$$

FFT for each segment

$$x_m[n] = \sum_{n=0}^{L-1} x_m^w[n] \cdot e^{j\frac{2p}{L}kn} \quad (5)$$

Periodogram for each segment

$$P_m[k] = \frac{1}{L \cdot f_s}\left|X_m[k]\right|^2 \quad (6)$$

Averaging the PSD (Welch estimate)

$$PSD_{Welch}[k] = \frac{1}{M}\sum_{m-1}^{M} P_m[k]$$

Mathematical comparison of FFT and Welch methods:**Table.2.**

Feature	**Standard FFT**	**Welch Method**
Spectral accuracy	Moderate	High
Variance	High	Low
Noise immunity	Low	High
Computational complexity	Low	Moderate
Suitability for EEG analysis	Limited	Very high

Rhythm power based on the PSD function:
where f1 and f2 are the frequency boundaries of the rhythm (for example, Alpha: 8–13 Hz).
The FFT serves as the primary mathematical model for spectral analysis, allowing the frequency components of an EEG signal to be identified. However, due to the high variance of its estimates, the Welch method is preferred for the stable analysis of sports EEG signals. By applying segmentation and averaging, the Welch algorithm increases the statistical reliability of the PSD estimate and ensures high accuracy when assessing the functional state of athletes.
The algorithm to be developed in this research is aimed at providing an effective method for the spectral analysis of EEG signals. For real-time use of this algorithm, the processes of signal acquisition, filtering, analysis, and visual display of results must be optimized. This software tool will allow

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monitoring of the athlete's brain activity and overall condition. In developing the algorithm, it is necessary to ensure a high level of accuracy while also using complex mathematical models to improve efficiency.
Various algorithms and methods are applied in the analysis of EEG signals:

- **Fast Fourier Transform (FFT):** used to convert the EEG signal from the time domain to the frequency domain and to analyze the spectral composition of the signal. Using the FFT, the dominant frequencies present in the signal can be identified.
- **Wavelet transform:** this method allows for a more localized time-frequency analysis of EEG signals. It is particularly useful for finer, more detailed signal analysis.
- **Independent Component Analysis (ICA):** used to separate mixed components within EEG signals. This is especially helpful for filtering out muscle activity and other types of interference.

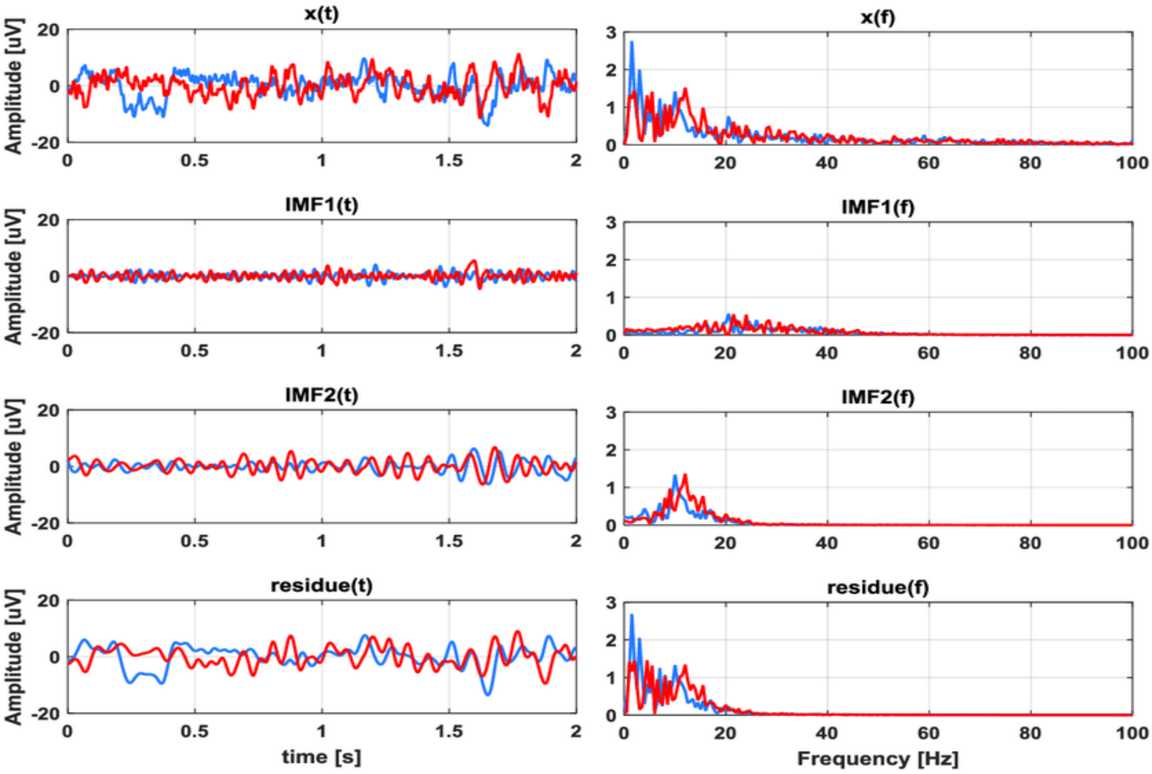

Fig.1.Time and Frequency Domain Representations of EEG Signal with IMF Components and Residue

- EEGLAB: a software tool built on MATLAB, used for analyzing EEG signals. It supports a variety of algorithms and analysis methods, including spectral analysis and ICA.
- BCILAB: a software tool designed for EEG signal analysis and for building Brain-Computer Interface (BCI) systems. BCILAB supports numerous signal processing techniques and provides capabilities for running them in real time.

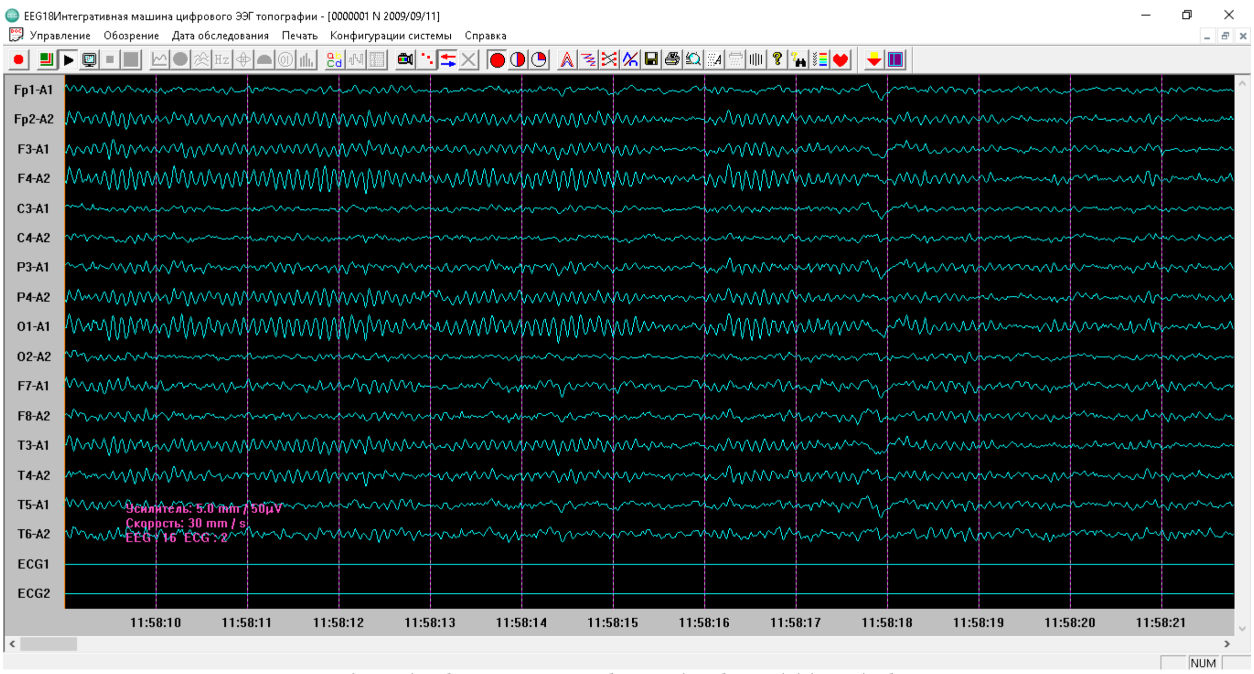

Fig.2. Simultaneous EEG and ECG Signal Acquisition Display

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Advantages of using EEG signals for athletes:

- Improving mental state: ensuring high performance of the athlete by reducing stress and optimizing mental condition.
- Increasing motivation: identifying the athlete's motivation through EEG signals and organizing individual exercises accordingly.
- Monitoring the rehabilitation process: tracking and improving the recovery process from injuries by analyzing the state of brain activity.
- Individualizing training programs: creating a training program tailored to each athlete by monitoring EEG signals.

Python and MATLAB environments were selected for digital processing and spectral analysis of EEG signals. These environments are widely used in scientific computing, signal processing, and data visualization.

Advantages of the Python environment:

- open source and free to use;
- availability of libraries such as NumPy, SciPy, MNE, and Matplotlib;
- capability for real-time analysis.

Advantages of the MATLAB environment:

- Signal Processing Toolbox;
- ready-made functions specifically for EEG analysis;
- user-friendly graphical interface.

Software module architecture

The developed software tool was designed using a modular architecture. Each module performs an independent task and is connected to the overall system.

Main modules:

- Data loading module
- Preprocessing module
- Spectral analysis module
- EEG rhythm extraction module
- Visualization module
- EEG data loading and formatting module

This module reads EEG signals from .edf, .csv, and .mat formats and converts them into a uniform structure.

IV. Conclusion

The analyses presented in this study show that achieving high results in athletes depends not only on physical fitness but also significantly on the functional state of the central nervous system. Electroencephalography (EEG), as a non-invasive, safe, and highly informative diagnostic tool, is one of the main methods for assessing brain activity. It makes it possible to determine an athlete's level of attention, fatigue, stress, and psycho-physiological strain. At the same time, the complex, noise-prone, and rapidly time-varying nature of EEG signals makes it difficult to evaluate them using traditional spectral analysis methods.

Existing spectral analysis techniques, particularly the FFT and Welch algorithms, do not adequately capture the dynamic characteristics of EEG signals. As a result, the accuracy of assessing an athlete's true functional state decreases, and decision-making becomes more subjective. To address these shortcomings, developing new, adaptive spectral analysis algorithms that account for individual athlete characteristics and are suitable for real-time operation has become a pressing scientific and practical issue. Combining advanced methods such as wavelet transform and Independent Component Analysis (ICA) with spectral analysis can lead to significantly better results.

Implementing the developed algorithms in the form of a software tool enables their widespread adoption in sports medicine and practical sports activities. Within the framework of this research, a software module with a modular architecture was created using Python and MATLAB environments. This module automatically handles EEG signal loading, filtering, spectral analysis, and visual display of results. For Power Spectral Density (PSD) calculation, the Welch method provides high statistical reliability through segmentation and averaging. Experiments have shown that spectral indicators obtained from cleaned EEG signals allow for an objective assessment of athletes' functional states.

In conclusion, this dissertation work proposes a scientifically grounded and practically convenient method for assessing athletes' psycho-physiological states based on EEG. The proposed spectral analysis algorithm and software tool help overcome the limitations of existing methods, enable an individualized approach to athlete training, and reduce the risk of injury. Future work plans include developing a version of this system that operates in real time, is adapted for mobile devices, and is supplemented with extended neurophysiological indicators.

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