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ANALYSIS OF INVOLUNTARY MOVEMENTS OF PATIENTS WITH TREMOR SYMPTOMS UNDER THE INFLUENCE OF COGNITIVE INFLUENCES

This study introduces a cutting-edge digital approach to analyzing the relationship between involuntary movements and brain activity in patients with neurological disorders associated with tremor, such as Parkinson's disease. The research was conducted on real patients, offering a practical perspective on how cognitive influences impact motor control and brain function. To achieve this, patients were asked to draw spirals on a Huion KAMVAS Pro 16 graphics tablet, a device equipped with a touch-sensitive screen and stylus, allowing for precise tracking of movement. Simultaneously, their brain activity was monitored using the NEUROCOM EEG system, with electrodes positioned on the posterior region of the head-an area strongly involved in motor coordination. This dual setup ensured synchronized data collection of motor performance and neural dynamics.

The primary goal of the study was to uncover connections between involuntary movements, observed as tremor-induced irregularities in the spiral drawings, and specific patterns of brain activity recorded through EEG. By comparing the data collected in medicated and unmedicated states, significant variations in tremor severity and brain function were identified. Key regions of the brain involved in motor regulation were identified, shedding light on the mechanisms that underlie tremor development and its modulation under different conditions.

This approach offers a groundbreaking perspective on the diagnosis and treatment of tremor-related conditions. Unlike traditional methods, which often rely on subjective assessments and are limited in capturing real-time neural activity, this method provides a more objective and detailed analysis of motor impairments. By integrating precise movement data from the graphics tablet with neurophysiological signals from EEG, the study demonstrates the potential for creating more effective, personalized treatment strategies for conditions like Parkinson's disease. The findings open new avenues for leveraging digital tools in clinical research, enabling a deeper understanding of how motor and cognitive processes interact in patients with tremor symptoms.

Key words: tremor, EEG, cognitive influences, motor control, graphics tablet, essential tremor, Parkinson's disease.

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АНАЛІЗ МИМОВІЛЬНИХ РУХІВ ПАЦІЄНТІВ ІЗ СИМПТОМАМИ ТРЕМОРУ ПІД ВПЛИВОМ КОГНІТИВНИХ ВПЛИВІВ

У дослідженні представлено сучасний цифровий підхід до аналізу взаємозв'язку між мимовільними рухами та активністю мозку в пацієнтів із неврологічними розладами, пов'язаними з тремором, як-от хвороба Паркінсона. Дослідження проводилося на реальних пацієнтах, що забезпечує практичний погляд на те, як когнітивні впливи діють на моторний контроль і функцію мозку. Пацієнтам пропонувалося малювати спіралі на графічному планшеті Huion KAMVAS Pro 16, обладнаному сенсорним екраном і стилусом для точного відстеження рухів. Водночас їх мозкову активність реєстрували за допомогою системи NEUROCOM EEG із розташуванням електродів у задній частині голови – ділянки, тісно пов'язаної з моторною координацією. Такий підхід забезпечив синхронізований збір даних про моторну діяльність та нейродинаміку.

Основна мета дослідження – виявити взаємозв'язки між мимовільними рухами, що проявлялися як порушення в малюнку спіралі, спричинені тремором, і специфічними патернами мозкової активності, зафіксованими на ЕЕГ. Порівнюючи дані пацієнтів у стані приймання медикаментів та без них, дало змогу виявити значні відмінності в тяжкості тремору та функції мозку. Визначено ключові ділянки мозку, залучені до регуляції моторики, що допомогло глибше зрозуміти механізми розвитку тремору та його модифікації за різних умов.

Цей підхід пропонує революційний погляд на діагностику та лікування станів, пов'язаних із тремором. На відміну від традиційних методів, які часто базуються на суб'єктивних оцінках і мають обмеження в реєстрації нейронної активності в реальному часі, цей метод надає більш об'єктивний і детальний аналіз моторних порушень. Інтеграція точних даних про рухи, отриманих із графічного планшета, та нейрофізіологічних сигналів з ЕЕГ демонструє потенціал для створення ефективніших і персоналізованих стратегій лікування таких станів, як хвороба Паркінсона. Отримані результати створюють нові перспективи для використання цифрових

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інструментів у клінічних дослідженнях, сприяючи глибшому розумінню взаємодії моторних і когнітивних процесів у пацієнтів із симптомами тремору.

Ключові слова: тремор, ЕЕГ, когнітивні впливи, контроль рухів, графічний планшет, есенціальний тремор, хвороба Паркінсона.

Introduction

Parkinson's disease (PD) is one of the most prevalent neurodegenerative disorders, affecting millions of individuals worldwide [2]. It is characterized by motor symptoms such as tremor, bradykinesia, rigidity, and postural instability, significantly impairing quality of life. Among these, tremor is one of the most prominent and disruptive symptoms, often resistant to conventional medication and challenging to manage effectively. Similarly, other neurological conditions such as Essential Tremor and various movement disorders also present with tremor, further complicating diagnosis and treatment.

Understanding the neurophysiological mechanisms underlying tremor is crucial for developing effective interventions. Recent advances in non-invasive techniques, such as electroencephalography (EEG), provide valuable insights into the brain's activity during motor tasks and have shown promise in assessing tremor characteristics. The integration of EEG with precise motor recording tools, like graphics tablets, allows researchers to capture real-time data on how the brain and motor systems interact in patients with tremor [1].

This study aims to explore the relationship between limb tremor and brain activity by synchronizing EEG data with motor performance during a controlled drawing task. By investigating how cognitive influences and medication impact tremor severity and neural activity, this research seeks to improve our understanding of tremor dynamics and support the development of more targeted and effective treatment strategies for patients with movement disorders.

Analysis of Research on the Problem of Involuntary Movement Disorders

Emerging information technologies and advanced modeling methods have significantly enhanced the development of computerized diagnostic systems, addressing critical health challenges worldwide. These advancements are particularly impactful for neurological conditions characterized by involuntary movement disorders (IMD), such as tremors and severe forms associated with diseases like Alzheimer's and Parkinson's. IMDs refer to involuntary oscillatory movements of specific body parts (e.g., hands, speech organs, or eyes) caused by involuntary muscle contractions. Key indicators of motor regulation disorders include increased movement amplitude, altered frequency, and irregular oscillation patterns.

Analyzing these parameters is crucial for understanding how feedback dysfunction in the neural nodes of the cerebral cortex influences cognitive motor control and for early detection of neuromotor disorders. However, identifying IMDs remains challenging due to the limitations of existing diagnostic methods, which suffer from low accuracy and a lack of mathematical and software tools to model the feedback effects of cortical neural nodes on movement behavior.

Numerous studies, including those by researchers such as Legrand A.P., Vidailhet M. (ESPCI Paris Tech, ICEM CNRS), Wang J.-S., Louis E., Haubenberger D., and Kalowitz D., have focused on analyzing patient behavior and movement parameters. Most of these studies employed traditional digital signal processing techniques, such as Fourier transforms, to evaluate patient conditions relative to normal baselines. However, these classical approaches are now considered inadequate for analyzing complex, unpredictable movement patterns often observed in patients with severe tremors. Such methods fail to capture a significant portion of critical information about the patient's condition, leading to reduced diagnostic quality and limited insights into real-world scenarios.

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Research Objective

The objective of this study is to develop a hybrid analytical model capable of accurately identifying and analyzing involuntary movement disorders (IMD) by leveraging advanced digital and neurophysiological data integration. The approach focuses on capturing and modeling the intricate relationship between cognitive feedback signals from the cerebral cortex and motor trajectories.

This research utilized fragments of spiral-type trajectories generated by patients (referred to as T-objects) using an electronic pen on an interactive graphics tablet. The captured motor data was combined with synchronized EEG signals recorded from cortical regions responsible for motor control. A hybrid ANM model was employed to decompose the movement trajectories into segments, allowing the identification of parameters associated with cognitive feedback effects reflected in the EEG signal vector.

The goal of this model is to achieve detailed decomposition of the system while preserving its integrity and interconnections-something that traditional signal processing methods fail to accomplish effectively. Classical approaches often lead to the loss of a significant portion of critical data, limiting diagnostic accuracy and insights into the patient's real condition.

To enhance the model's performance, machine learning techniques are incorporated to refine the weight coefficients of cognitive feedback signals recorded during the spiral trajectory test. This ensures more accurate mapping of neural influences on motor behavior, enabling precise characterization of the patient’s condition and providing a foundation for improving diagnosis and treatment of neurological disorders involving involuntary movements.

Development Methodology

The proposed methodology for digital diagnostics of involuntary movement disorders (IMD) leverages advanced information technology to integrate motor performance tracking with neurophysiological data. The system continuously monitors the position of the patient's hand using an interactive, high-resolution tablet paired with an electronic pen. Simultaneously, it records cognitive neuro signals from specific regions of the cerebral cortex, which are responsible for generating and modulating oscillatory movements. These signals are captured via sensors embedded in a specialized EEG helmet worn by the patient during the test.

During the diagnostic process, patients trace predefined test trajectories, such as spirals, on the tablet. The system synchronizes the electronic pen's position and pressure data with real-time readings from the cortical neuro nodes, ensuring precise alignment between motor actions and cognitive activity. All collected data is stored in a digital format for subsequent analysis.

To interpret this data, a hybrid analytical framework combining Fourier-based wave signal analysis and advanced computational techniques is employed. This model decomposes the recorded signals to identify the interplay between involuntary motor disturbances (IMDs) and the cognitive influences from the cerebral cortex. The approach enables a detailed examination of movement irregularities and their underlying neurophysiological causes, providing insights that are unattainable through traditional diagnostic methods.

This methodology, described in greater detail in our subsequent works, highlights the potential of combining high-resolution motion capture with neuro-cognitive feedback analysis for improved diagnosis and treatment of disorders characterized by abnormal motor and cognitive interactions. By integrating these technologies, the system achieves a robust, synchronized platform for analyzing complex neurological phenomena.

Hardware Overview. Movement Data Collection Using a Graphics Tablet

For the quantitative assessment of patient movement, the Huion KAMVAS Pro 16 graphics tablet was used, which captures the position and pressure of the stylus in real-time throughout the experiment. While typically used for artistic purposes, this tablet was adapted with custom software

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to record the X and Y coordinates as a function of time. The tablet provides high precision, with data accuracy and frequency dependent on the tablet's specifications, making it suitable for detailed movement analysis.

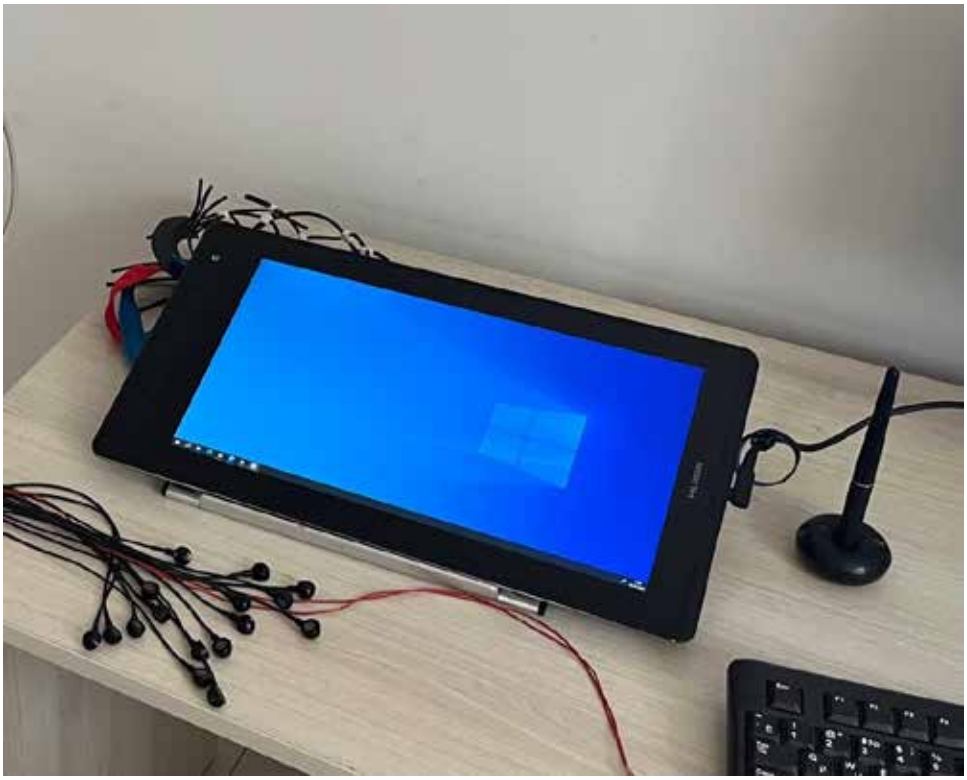

Fig. 1. Huion KAMVAS Pro 16 graphics tablet

NeuroCom Electroencephalography System by KHAI-MEDYKA

The study employed the NEUROCOM computer electroencephalography (EEG) system, developed by KHAI-MEDYKA, to record brain signals [6]. This fifth-generation EEG system is designed for detailed analysis and interpretation of EEG signals, including evoked potentials, which are essential for scientific research.

Fig. 2. The data collection process from the NeuroCom electroencephalography complex

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Fig. 3. Demonstration of using research hardware

The system includes a 16-channel electrode helmet that transmits EEG data to a personal computer in real-time. Data is collected at a frequency of 500 Hz (2 ms intervals) and processed through specialized software. The EEG signals are conditioned and post-processed on the PC, with the data stored in both raw text and visual formats for further analysis.

Methods and Participants

The study included five anonymized patients diagnosed with various neurological conditions characterized by tremor. Each participant completed the experimental task involving spiral drawing under different conditions, resulting in a total of 18 trials across all participants. One patient was tested twice in two separate sessions to assess the effect of medication on tremor, providing six trials in total.

1. Patient A (Female, Age 50–60):

• Diagnosis: Parkinson's Disease, Stage 3 (Hoehn and Yahr scale), with moderate akinetic syndromes and severe limb tremor.

• Session Details: This patient performed three trials in the morning after taking medication and three additional trials in the afternoon, once the medication's effects had diminished, showing pronounced tremor. This allowed for comparative analysis under medicated and unmedicated states.

2. Patient B (Female, Age 70280):

• Diagnosis: Parkinson's Disease, Stage 2 (Hoehn and Yahr scale), with moderate akinetic syndromes and mild tremor in the right limbs.

• Session Details: The patient completed three trials without complications, with mild tremor symptoms observed during the tasks.

3. Patient C (Male, Age 70280):

• Diagnosis: Parkinson's Disease, Stage 3 (Hoehn and Yahr scale), with moderate akinetic syndromes and pronounced limb tremor.

• Session Details: The patient had vision difficulties, which impacted his ability to draw a precise spiral. For this patient, the analysis focused on movement patterns rather than strict adherence to the spiral shape.

4. Patient D (Male, Age 30–40):

• Diagnosis: Extrapyramidal tremor of unspecified origin.

• Session Details: The patient completed the task three times, showing tremor characteristics associated with non-specific extrapyramidal disorders, possibly influenced by work-related stress and digestive issues.

5. Patient E (Female, Age 50–60):

• Diagnosis: Sequelae of meningoencephalitis with choreiform hyperkinesia of the right arm.

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• Session Details: The patient also had vision problems, which affected her ability to follow the spiral pattern. The analysis concentrated on movement irregularities linked to her neurological condition.

Experimental Procedure

Participants performed a spiral drawing task on a Huion KAMVAS Pro 16 graphics tablet, which recorded their hand movements in real-time. Each participant performed the task three times per session, except for Patient A, who completed two sessions, resulting in six trials.

Data Acquisition

1. Graphics Tablet Data:

• The graphics tablet captured detailed movement data, including the trajectory, speed, and deviations from the intended path, allowing for an in-depth analysis of tremor characteristics.

2. EEG Recording:

• EEG data were collected using the NEUROCOM system with 16 electrodes placed on the occipital and parietal lobes, areas known for their involvement in motor control and sensory processing. Two additional electrodes (reference and ground) were positioned near the ears to stabilize and reduce noise in the signal.

Synchronization and Data Collection

Both the graphics tablet and EEG data were synchronized using shared timestamps, enabling precise temporal analysis of the relationship between observed motor tremor and neural activity.

Ethical Considerations

Patient privacy and confidentiality were strictly maintained, with all data anonymized and securely handled as part of routine assessments. No personal or identifying information was disclosed, ensuring full compliance with ethical standards.

EEG Recording and Preprocessing

• EEG System and Setup: Description of the NEUROCOM EEG system, electrode placement focusing on the occipital and parietal lobes, and the role of REF and GND electrodes near the ears.

• Electrode Placement Rationale: Explanation of the posterior brain regions' involvement in motor control, referencing existing literature.

• Data Synchronization: Details on synchronizing EEG and graphics tablet data using shared timestamps for accurate temporal analysis.

Hybrid Model for Analyzing Involuntary Movement Disorders with Cognitive Neurofeedback

This hybrid model analyzes involuntary movement disorders (IMD) by segmenting hand movements based on wave signal propagation. The system captures hand trajectories via an electronic pen drawing an Archimedean spiral on an interactive tablet. Deviations from the template provide data on the patient’s neurological condition. The complex pen movement is broken into smaller segments, allowing for detailed analysis of IMD. Cognitive neurofeedback from the cerebral cortex (CC) is integrated through EEG signals, which are synchronized with the pen's movement [10]. This model offers quantitative insights into the amplitude and frequency of IMD, and the segmentation process can be adjusted based on the complexity of the movement.

Digital Analysis of IMD Limb Movement Trajectories

It represents a model-based approach formulated in matrix form, which calculates the position of an electronic pen on an interactive tablet. The matrix expressions enable efficient computation, including parallel processing of data.

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The experimental setup used for capturing EEG signals and involuntary movement during a drawing task. Participants trace a spiral pattern on a graphics tablet/monitor using a stylus, while EEG signals are recorded via electrodes attached to their scalp. The system synchronizes the motor data with the EEG signals, allowing the extraction of features related to motor control and cognitive feedback mechanisms.

$$\begin{bmatrix} u_1(t_1,l_1) \\ u_2(t_2,l_2) \\ \dots \\ u_j(t_j,l_j) \\ \dots \\ u_{n+1}(t_{n+1},l_{n+1}) \end{bmatrix} = \begin{bmatrix} \Gamma_{11}(t_1,l_1,l_1) & & & & \\ \Gamma_{21}(t_1,l_2,l_1) & \Gamma_{22}(t_2,l_2,l_2) & & & \\ & \dots & & & \\ \Gamma_{j1}(t_1,l_j,l_1) & \Gamma_{j2}(t_2,l_j,l_2) & \dots & \Gamma_{jj}(t_j,l_j,l_j) & 0 \\ & \dots & & & \\ \Gamma_{n+1,1}(t_1,l_{n+1},l_1) & \Gamma_{n+1,2}(t_2,l_{n+1},l_2)\bar{S}(t_2) & \dots & \Gamma_{n+1,j}(t_j,l_{n+1},l_j) & \dots \\ \Gamma_{n+1,n+1}(t_{n+1},l_{n+1},l_{n+1}) & & & & \end{bmatrix} \cdot$$

$$\cdot \begin{bmatrix} S_{1_1}(t_1) & S_{2_1}(t_1) & \dots & S_{m_1}(t_1) \\ S_{1_2}(t_2) & S_{2_2}(t_2) & \dots & S_{m_2}(t_2) \\ \dots & \dots & \dots & \dots \\ S_{1_j}(t_j) & S_{2_j}(t_j) & \dots & S_{m_j}(t_j) \\ \dots & \dots & \dots & \dots \\ S_{1_{n+1}}(t_{n+1}) & S_{2_{n+1}}(t_{n+1}) & \dots & S_{m_{n+1}}(t_{n+1}) \end{bmatrix} \cdot \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \dots \\ \alpha_i \\ \dots \\ \alpha_m \end{bmatrix} \quad (1)$$

Range of matrices and vectors used in the model.

Vector of Amplitude Deviations: Represents the deviation of IMD movements from standard trajectories (e.g., Archimedean spirals): $\left[u_j(t_j,l_j)\right]$, $j=\overline{1,n+1}$. The vector captures geometric coordinates along the trajectory at specific time intervals, segmenting the IMD path into elementary motion components. l_j, t_j – the geometric coordinate along the movement trajectory aligns with the Archimedean spiral's linear transformation. Its position depends on the elapsed time associated with the trajectory. The variable j acts as an index that identifies the sequence of elementary segments within the IMD trajectory. Additionally, n indicates the total number of division points along the IMD trajectory, breaking it into simpler, smaller motion segments.

Feedback Impact Matrix: Quantifies how cognitive signals influence individual IMD trajectory segments. It is calculated as follows:

$$\left[\Gamma_{ji}(t_i,l_j,l_i)\right] = \sum_{m=1}^{\infty}\left[\left(1-\cos\left(\frac{\beta_m t_i}{b_i}\right)\right)/\left(\beta_m/b_i\right)^2 V_j\left(l_j,\beta_m\right)\bar{V}_i\left(\beta_m\right)/\left|V\left(l_j,\beta_m\right)\right|^2\right], \; {}_{j,i=\overline{1,n+1}} \quad (2)$$

Here, b_i represents the amplitude characteristic for the *i*-th segment of the IMD trajectory, β_m, $m=\overline{0,\infty}$ corresponds to the components of the spectral hybrid Fourier function, and the associated set of spectral values.

Cognitive Signal Matrix: Contains the values of signals collected from sensors positioned on neural nodes of the cerebral cortex via an EEG helmet.

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The matrix links the signals to specific segments of the IMD trajectory, enabling detailed feedback analysis: $\left[s_{i_j}(t_j) \right],\ i=\overline{1,m},\ j=\overline{1,n+1}$.

Adaptive Coefficient Vector: Represents the influence of cognitive signals from each EEG sensor on IMD movement elements. These coefficients are calculated using an algorithm described in the subsequent matrix formulation: $\left[\alpha_i \right],\ i=\overline{1,m}$.

Analytical Solution

Through matrix computations, an analytical vector solution is derived, establishing a direct relationship between amplitude deviations in IMD and the cognitive signal values over time. The model incorporates both immediate sensor readings and residual effects of prior signal states, offering a dynamic view of cognitive feedback on motor performance.

$$\begin{bmatrix} u_1(t_1,l_1) \\ u_2(t_2,l_2) \\ \dots \\ u_j(t_j,l_j) \\ \dots \\ u_m(t_m,l_m) \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{m} \alpha_i \Gamma_{1i}(t_1,l_1,l_1) S_{i_1}(t_1) \\ \sum_{i=1}^{m} \alpha_i \left(\Gamma_{21}(t_1,l_2,l_1) S_{i_1}(t_1) + \Gamma_{22}(t_2,l_2,l_2) S_{i_2}(t_2) \right) \\ \dots \\ \sum_{i=1}^{m} \alpha_i \left(\Gamma_{j1}(t_1,l_j,l_1) \cdot S_{i_1}(t_1) + \Gamma_{j2}(t_2,l_j,l_2) \cdot S_{i_2}(t_2) + \dots + \Gamma_{jj}(t_j,l_j,l_j) \cdot S_{i_j}(t_j) \right) \\ \dots \\ \sum_{i=1}^{m} \alpha_i \begin{pmatrix} \Gamma_{m1}(t_1,l_m,l_1) S_{i_1}(t_1) + \Gamma_{m2}(t_2,l_m,l_2) S_{i_2}(t_2) + \dots + \Gamma_{mj}(t_j,l_m,l_j) S_{i_j}(t_j) + \dots \\ + \Gamma_{mm}(t_m,l_m,l_m) S_{i_m}(t_m) \end{pmatrix} \end{bmatrix} \quad (3)$$

This dependency enables precise tracking of feedback effects from EEG sensor data on each segment of the IMD trajectory, considering real-time values and cumulative aftereffects. Such a detailed analytical framework significantly enhances the understanding of cognitive-motor interactions and provides a robust basis for evaluating neurological disorders.

Impact of Medication on Tremor Control: A Comparative Analysis of Spiral Drawings

The comparison between the medicated and unmedicated spirals reveals a notable difference in motor control. In the medicated state, the spiral appears smoother, with fewer deviations from the intended path, indicating improved coordination and reduced tremor. The unmedicated spiral, however, exhibits significant irregularities, with sharp oscillations and tremor-related disruptions. These visible tremor patterns highlight the lack of motor stability when medication is not administered. This comparison underscores the role of medication in managing neurological conditions by providing patients with better control over involuntary movements, significantly enhancing their ability to perform precise tasks.

Figure 4 shows the results of two computer testing sessions for a patient diagnosed with Parkinson's disease, Stage 3 according to the Hoehn and Yahr scale, conducted after taking the prescribed dose of medication. As seen in the figure, the trajectory of the patient's hand movement with the electronic pen on the graphics tablet is relatively stable, reflecting a calmer state of the patient. These results indicate minimal tremor during the two drawing attempts, which corresponds to a controlled motor state due to the lasting effects of the medication. The deviation analysis of the patient's hand movement for these two attempts is shown in Figure 6.

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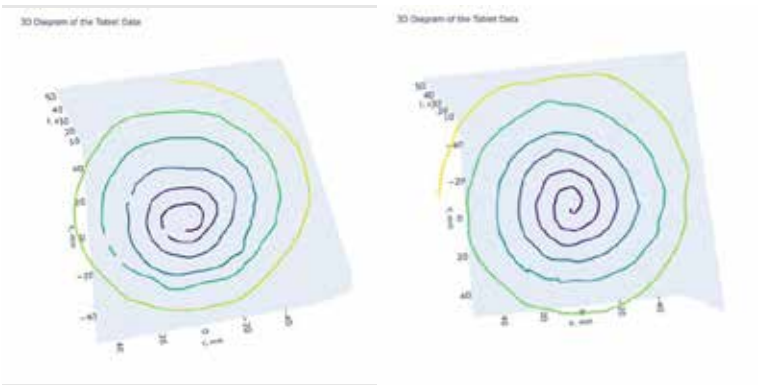

Fig. 4. Spiral Drawings. Patient A with medication (attempts 2 and 3)

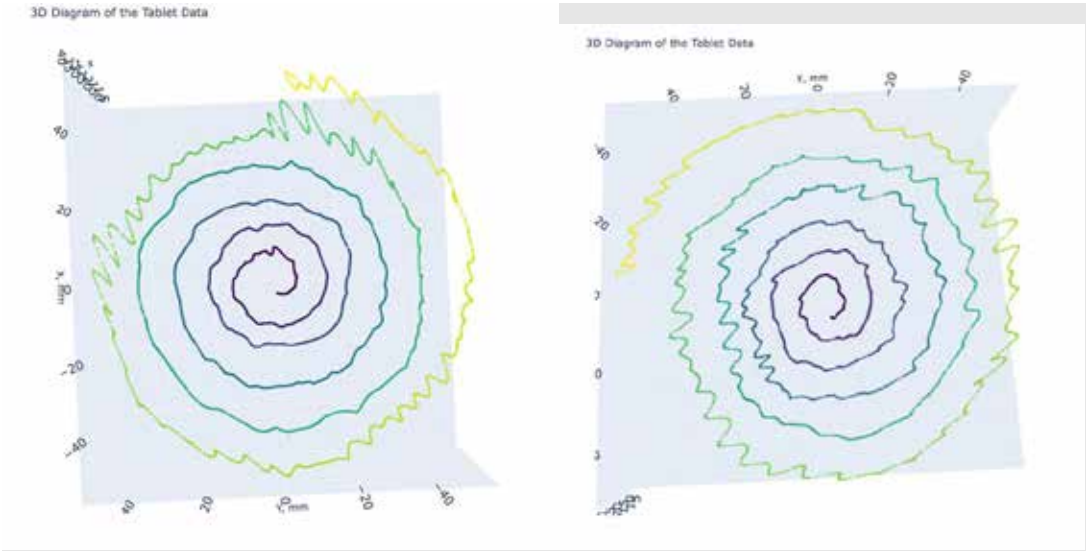

Fig. 5. Spiral Drawings. Patient A without medication (attempts 5 and 6)

Figure 5 presents the results of the next two computer testing attempts conducted by the same patient, a few hours after the initial session. By this time, the medication's effects had worn off, resulting in a noticeable increase in tremor severity. As shown in Figure 5, the trajectory of the hand movement with the electronic pen on the graphics tablet initially exhibits minor tremors, which intensify as the movement progresses. This increase in tremor is likely due to the patient's agitated state. The worsening tremor highlights the reduced motor control as the medication's effects diminished. A detailed analysis of the deviations in the patient's hand movement trajectories for both attempts is provided in Figure 7.

Figure 6 illustrates the measured R values and the Gaussian filter-based fitting of the R data for Patient A under the influence of medication (attempts 2 and 3). The plot displays two curves: the raw measured R values, which represent the radial distance from the center of the spiral as a function of the angle θ, and the smoothed R values obtained using a Gaussian filter. The smoothing process helps reduce noise in the data, providing a clearer representation of the underlying movement pattern. The smoother curve highlights the overall trajectory of the hand movement with reduced tremor, reflecting the patient's improved motor control under medication. The comparison between the raw and fitted curves offers insight into the consistency of the hand movements and the effectiveness of the smoothing technique.

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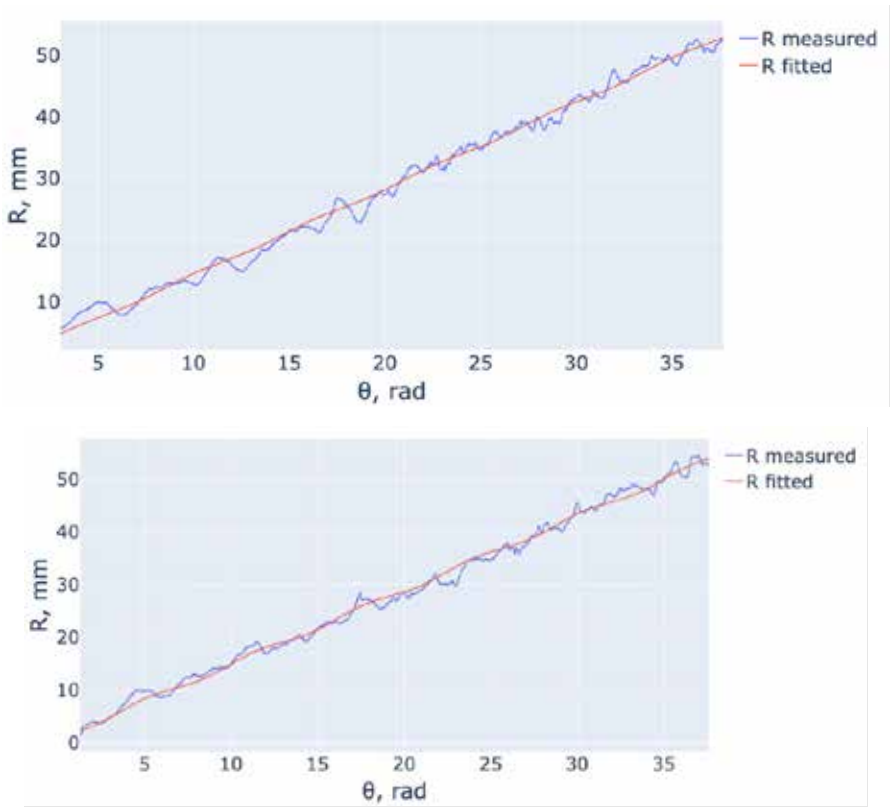

Fig. 6. Measured R values and Gaussian filter-based fitting of R data. Patient A with medication (attempts 2 and 3)

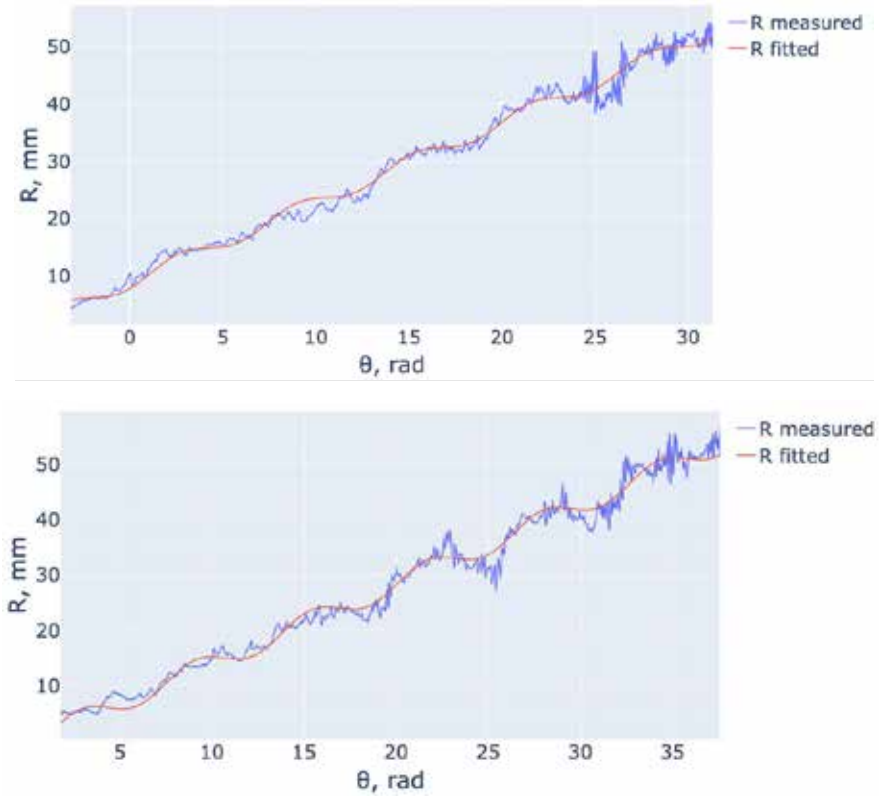

Fig. 7. Measured R values and Gaussian filter-based fitting of R data. Patient A without medication (attempts 5 and 6)

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Figure 7 shows the measured R values and the Gaussian filter-based fitting of the R data for Patient A without medication (attempts 5 and 6). The plot features two curves: the raw measured R values, representing the radial distance as a function of the angle θ, and the smoothed R values obtained using a Gaussian filter. In this case, the raw data exhibits more pronounced fluctuations, indicating increased tremor due to the absence of medication. The Gaussian-filtered curve smooths out some of these fluctuations, but the tremor's impact remains evident in the larger deviations from the ideal trajectory compared to the medicated state. This figure highlights the significant deterioration in motor control when medication is not administered.

Figure 8 shows the residual fluctuation $\Delta R = R_{measured} - R_{fitted}$ for Patient A with medication (attempts 2 and 3). It represents the difference between the raw and smoothed R values, highlighting remaining tremors or irregularities in hand movement. The x-axis shows time in seconds, and the y-axis shows ΔR in millimeters. The relatively small fluctuations indicate stable motor control with minimal tremor while the patient is on medication.

Figure 9 illustrates the residual fluctuation $\Delta R = R_{measured} - R_{fitted}$ for Patient A without medication (attempts 5 and 6). This shows the difference between the raw measured R values and the smoothed R values, highlighting the remaining tremors or irregularities in movement. The x-axis represents time in seconds, and the y-axis shows ΔR in millimeters. In contrast to the medicated state, the fluctuations here are much larger, indicating more pronounced tremor and less controlled hand movement without medication.

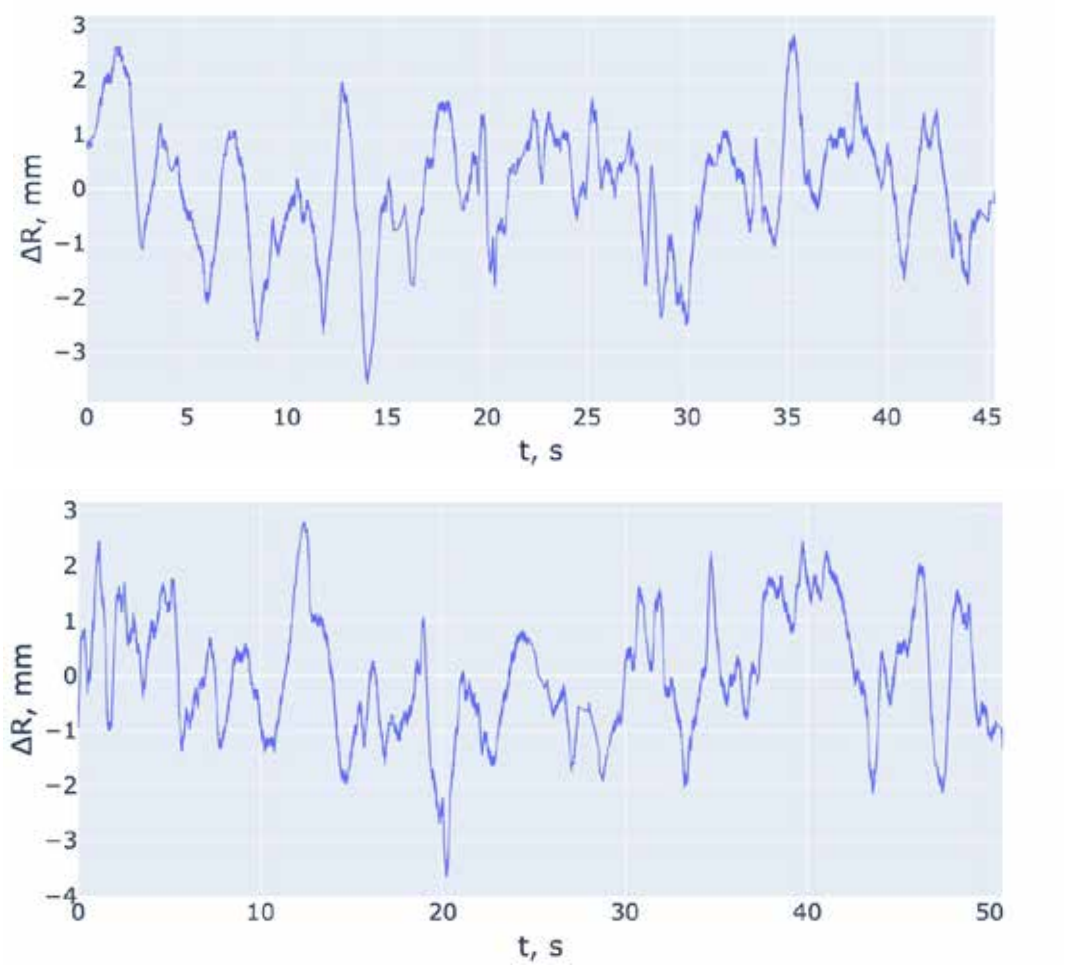

Fig. 8. Residual fluctuation ΔR = R measured – R fitted. Patient A with medication (attempts 2 and 3)

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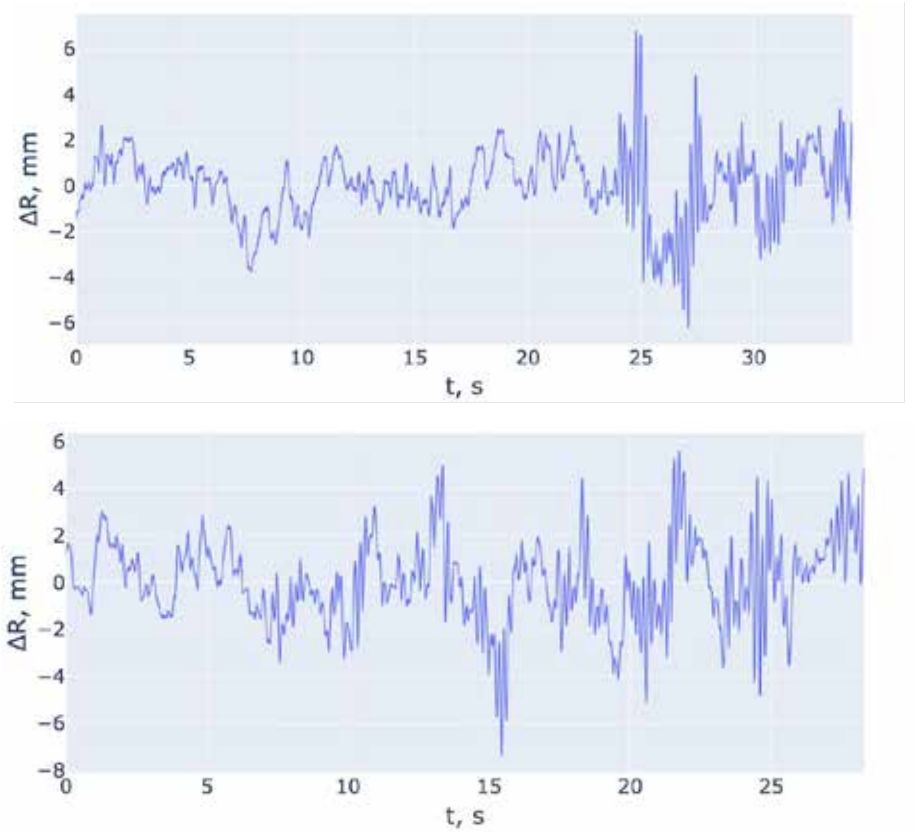

Fig. 9. Residual fluctuation ΔR = R measured – R fitted. Patient A without medication (attempts 5 and 6)

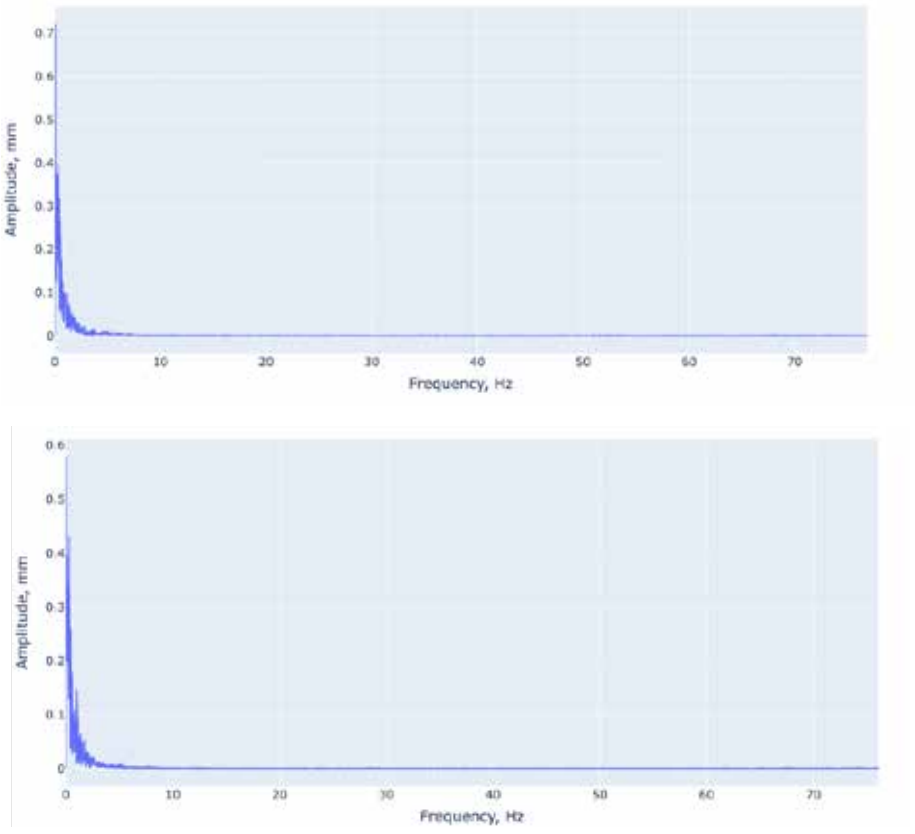

Fig. 10. Frequency decomposition. Patient A with medication (attempts 2 and 3)

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Figure 10 displays the frequency decomposition for Patient A with medication (attempts 2 and 3). This plot shows the breakdown of the residual fluctuations ΔR into their frequency components using a Fourier transform. The x-axis represents the frequency in Hertz (Hz), and the y-axis shows the amplitude of the oscillations in millimeters. The graph highlights the dominant frequency components of the patient's tremor while on medication, offering insights into the specific frequency ranges where tremor activity is most prominent. The relatively lower amplitude values indicate reduced tremor intensity due to the medication's effect on motor control.

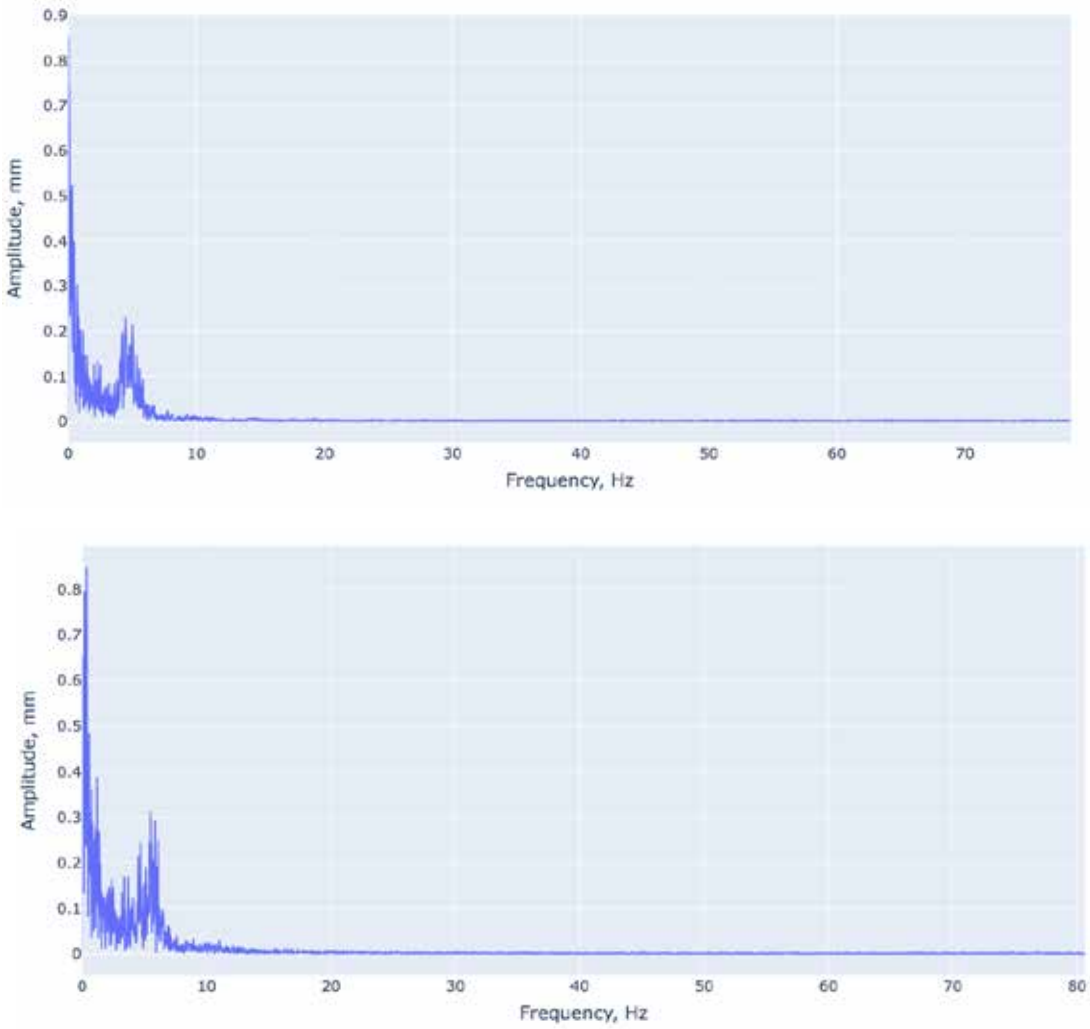

Fig. 11. Frequency decomposition. Patient A without medication (attempts 2 and 3)

Figure 11 presents the frequency decomposition for Patient A without medication (attempts 5 and 6). This plot breaks down the residual fluctuations ΔR into their frequency components using a Fourier transform. The x-axis represents frequency in Hertz (Hz), and the y-axis shows the amplitude of the oscillations in millimeters. In contrast to the medicated state, the amplitude values are significantly higher, indicating stronger tremor activity. The presence of pronounced peaks in certain frequency ranges reflects the increased severity of the patient's tremor when medication is not active.

The analysis of the spiral data involved calculating R values and fitting them using a Gaussian filter. The results show that under the influence of medication, the movement curve is smoother and more linear, indicating better motor control with minimal signs of tremor. In contrast, the unmedicated data shows significant fluctuations, which reflect the presence of tremor.

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To further analyze the movement, we calculated the fluctuation and performed frequency decomposition. The results show a clear peak at 4–6 Hz in the unmedicated condition, which is typical for tremor. In the medicated state, this peak is significantly reduced or absent, indicating effective tremor suppression and improved motor control. The graphs highlight this difference, with higher amplitudes in the 4–6 Hz range for the unmedicated condition and much lower amplitudes under medication.

Conclusions

The study introduces an advanced information technology approach for evaluating neurological movements based on a hybrid model that integrates wave signal analysis with cognitive feedback from the cerebral cortex. This method provides a detailed vector analysis of spiral drawing movements performed with an electronic pen on a digital tablet, allowing for precise identification of movement trajectories and feedback mechanisms without the substantial information loss typically seen in traditional signal processing. The analysis revealed clear differences between the medicated and unmedicated states. Frequency decomposition showed a significant peak at 4–6 Hz in the unmedicated condition, indicating tremor activity, which was significantly reduced or absent with medication. This highlights the effectiveness of medication in reducing tremor and improving motor control.

Overall, this approach offers a more detailed understanding of the neurological mechanisms behind involuntary movements, particularly under the influence of cognitive feedback from the nervous system, enhancing diagnostic accuracy and informing more effective treatment strategies.

The hybrid model analyzes wave signals of involuntary movements influenced by cerebral cortex neural nodes, enabling precise, rapid diagnosis of neurological disorders from injuries. It identifies affected brain regions and guides effective treatment to restore neurological function.

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