Вісник Тернопільського національного технічного університету
https://doi.org/10.33108/visnyk_tntu
Scientific Journal of the Ternopil National Technical University
2025, № 3 (119) https://doi.org/10.33108/visnyk_tntu2025.03
ISSN 2522-4433. Web: ***visnyk.tntu.edu.ua***

UDC 616.858-008.6:616.8-073.97:616.8-009.3

ALGORITHMIC APPROACH TO TREMOR CLASSIFICATION BASED ON EEG AND GRAPHOMOTOR SIGNALS

Dmytro Bishchak; Mykhaylo Petryk

Ternopil Ivan Puluj National Technical University, Ternopil, Ukraine

Abstract. *This study presents an algorithmic framework for tremor classification and differential diagnosis based on multimodal analysis of electroencephalographic (EEG) signals and graphomotor activity recorded during a spiral drawing task on a graphics tablet. Motor deviations were quantified using the ΔR metric, defined as the difference between the actual radial trajectory and its smoothed reference obtained via parametric curve fitting. EEG and graphomotor signals were synchronized and preprocessed through normalization and interpolation. All available EEG channels were included in the analysis to comprehensively capture cortical activity patterns. The method centers on cross-correlation analysis between ΔR and individual EEG channels to reveal spatiotemporal brain activity patterns associated with tremor, and introduces a sinusoidality index of cross-correlation curves as an indicator of cortical synchrony under different clinical conditions. Experimental results from patients with Parkinson's disease (medicated and unmedicated) and tremor of undetermined origin showed that pronounced tremor corresponds to higher inter-channel synchronization, whereas symptom reduction is marked by more independent EEG activity. The proposed approach combines quantitative computation with adaptability to individual patient profiles, and can serve as the basis for portable or cloud-based systems for automated tremor analysis and monitoring, expanding the capabilities of telemedicine and personalized neurodiagnostics. The proposed algorithmic approach integrates advanced software engineering techniques for multimodal signal synchronization, numerical analysis, and feature extraction, representing an applied solution at the intersection of biomedical data processing and computer science.*

Key words*: tremor, electroencephalography, electroencephalographic signal, EEG, graphomotor signals, ΔR, Parkinson's disease, frequency analysis, cross-correlation, classification, software, computer diagnostics, medical diagnostics, information system, datasets, time series, algorithm, adaptive software, adaptive system, digital platform, signal processing, estimation, normalization, automation.*

https://doi.org/10.33108/visnyk_tntu2025.03.035 *Received 10.07.2025*

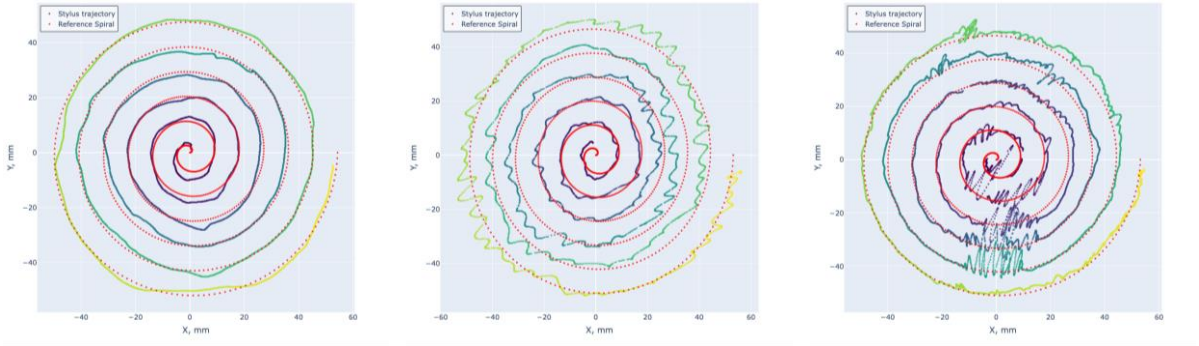
1. INTRODUCTION

Tremor is one of the most common and visible symptoms of a wide range of neurological disorders, including Parkinson's disease (PD), essential tremor (ET), dystonic tremor, and other movement disorders [11]. While tremor can often be observed during a clinical examination, its objective classification, quantitative assessment, and differential diagnosis remain challenging tasks in clinical neurophysiology. This is especially true in the early stages of disease, when motor disturbances are subtle, and visual inspection alone may not be sufficiently informative. In such cases, even experienced neurologists may need to rely on subjective judgments, which increases the risk of misdiagnosis or delayed intervention. From a software engineering perspective, the proposed framework demonstrates the implementation of a modular architecture for multimodal data acquisition, preprocessing, and cross-correlation computation, which aligns with current trends in intelligent information systems development.

Over the last two decades, advances in motion-tracking technologies and electroencephalography (EEG) have opened new opportunities for quantitative tremor assessment [12, 13] (see also [14]). High-resolution graphics tablets, wearable sensors, and portable EEG systems can now record precise hand movement trajectories, stylus pressure, tremor frequency and amplitude, as well as simultaneous cortical activity patterns. This

convergence enables a multimodal approach, combining motor output analysis with brain activity monitoring in a unified diagnostic framework.

Previous studies have shown that graphomotor analysis using the so-called ΔR index – the radial deviation from an ideal Archimedean spiral – can serve as a robust quantitative marker of motor instability. Frequency-domain analysis of ΔR makes it possible to identify characteristic spectral peaks corresponding to typical tremor frequency ranges: 4–6 Hz for Parkinson's disease tremor at rest [11], 6–10 Hz for essential tremor [12], and below ~4 Hz for various atypical or secondary tremors (including post-encephalitic and certain extrapyramidal forms) [14, 17]. In our dataset, active PD cases fell within the expected 4–6 Hz range, while other tremor types exhibited either no dominant peak or low-frequency oscillations (0.2–1 Hz), outside the classical PD/ET bands. These methods have already been validated in both research and clinical settings.



a b c

Figure 1. Spiral drawing: P1 medicated – a; P1 unmedicated – b; P2 unmedicated – c

However, analyzing the motor signal alone does not capture the full neurophysiological context of tremor. Tremor is the result of complex interactions between the cerebral cortex, subcortical structures, cerebellum, and the peripheral nervous system [19]. Identifying temporal and spatial patterns in brain activity that precede or accompany tremor episodes offers a more complete understanding of its pathophysiology.

One promising way to investigate such relationships is through cross-correlation analysis [18]. Cross-correlation measures the similarity between two signals as a function of temporal lag, making it particularly useful for detecting delays between neural activity onset and observable motor output. In this work, ΔR is treated as a motor marker, while EEG channels provide time-resolved information on cortical processes.

The novel contribution of our study lies in introducing a quantitative sinusoidality index computed for cross-correlation curves obtained between ΔR and each EEG channel. The reasoning is as follows: if a patient with tremor exhibits cross-correlation curves of similar shape across multiple EEG channels, this suggests that these cortical areas are participating in a coordinated, resonance-like neural pattern driving the tremor. Conversely, when tremor is absent or suppressed, the cross-correlation curves become less synchronized, reflecting more independent neural activity across cortical regions.

By calculating the sinusoidality index (SI) for cross-correlation curves of EEG channels, a single interpretable measure of the global sinusoidal tendency of cortical synchrony associated with tremor is obtained. This metric can then be compared across patient states – for example, before and after pharmacological treatment – to objectively quantify therapeutic effects. In our experiments, high Sinusoidality Index (SI) values (≈0.15–0.40) were observed

during active tremor, while significantly lower values (≈0.05–0.10) were found after medication-induced tremor suppression.

This approach offers several important advantages:

– Interpretability – The method produces visual outputs such as cross-correlation overlays that are intuitive for clinicians.

– Non-invasiveness – It uses existing non-invasive recordings (tablet and EEG) without additional procedures.

Compatibility with classical and AI-based methods – The SI metric can be used both in rule-based classification and as a feature for machine learning algorithms.

Sensitivity to pre-tremor activity – Changes in cortical synchrony may be detectable before tremor becomes visually apparent.

While machine learning approaches have been explored for tremor classification [1, 5] (see also [2–4, 6–10]), they often require large datasets, are sensitive to preprocessing variations, and lack transparency in clinical interpretation. The proposed rule-based framework, centered on cross-correlation and SI, strikes a balance between objectivity, reproducibility, and interpretability – making it suitable for both clinical application and further research integration.

The present study builds on earlier work in three ways:

It incorporates ΔR computation and frequency analysis as established markers of tremor presence and type.

It extends these methods with cross-correlation analysis between ΔR and EEG channels to capture temporal brain–motor relationships.

It introduces average pairwise cross-correlation similarity between EEG channels as a novel metric of tremor-related cortical synchrony.

Objective of the study: To develop and validate an algorithmic framework for tremor classification that combines motor deviation analysis (ΔR), spectral features, and a novel EEG synchrony metric (Sinusoidality Index, SI) derived from cross-correlation. This framework aims to improve differential diagnosis, enable monitoring of therapeutic effects, and serve as a foundation for portable or cloud-based tremor assessment systems.

In the following sections, we describe the experimental setup, data acquisition and synchronization process, signal preprocessing pipeline, cross-correlation analysis procedure, and the derivation of the Sinusoidality Index (SI). We then present results from patients with varying clinical profiles – including Parkinson's disease, medication-compensated tremor, and tremor of undetermined origin – and discuss the diagnostic implications and potential applications of the method.

2. MATERIALS AND METHODS, PROCESSING, AND RESULTS

This study examined four recording scenarios: Parkinson's disease (PD) without medication, the same patient after pharmacological treatment, PD with stable medication and minimal tremor, and tremor of undetermined origin. Each recording session consisted of a spiral-drawing task performed on a Huion Kamvas Pro 16 graphics tablet (sampling rate 250 Hz, sub-millimeter resolution) while EEG was simultaneously acquired from 16 scalp electrodes (Fp1–O2) at 500 Hz. The tablet application, implemented in Java using the JPen library [17], provided raw stylus coordinates (X, Y), pressure, and high-precision timestamps. EEG was recorded from 16 channels at a 500 Hz sampling rate, with electrodes positioned to emphasize the occipital region, which plays a key role in visual processing and motor coordination.

Tablet and EEG data were synchronized by aligning absolute timestamps to a common relative time base (t = 0 at trial start). EEG data were time-aligned to the tablet recordings using a common relative time axis.

The planar coordinates from the tablet were transformed into polar coordinates $R(t)$ and $\theta(t)$. A smooth fitted spiral model was obtained by curve fitting:

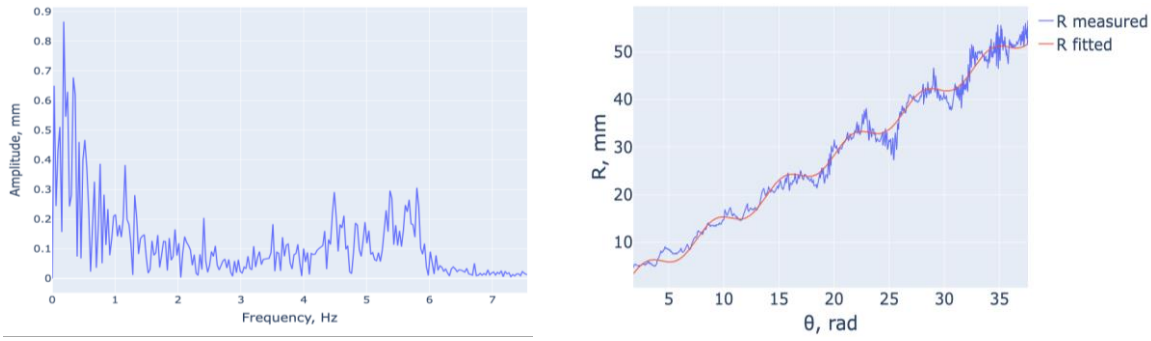
$$R_{smooth}(\theta) = a + b\theta + c \cdot cos(\theta) + d \cdot sin(\theta) \quad (1)$$

The radial deviation signal was defined as:

$$\Delta R(t) = R(t) - R_{smooth}\big(\theta(t)\big) \quad (2)$$

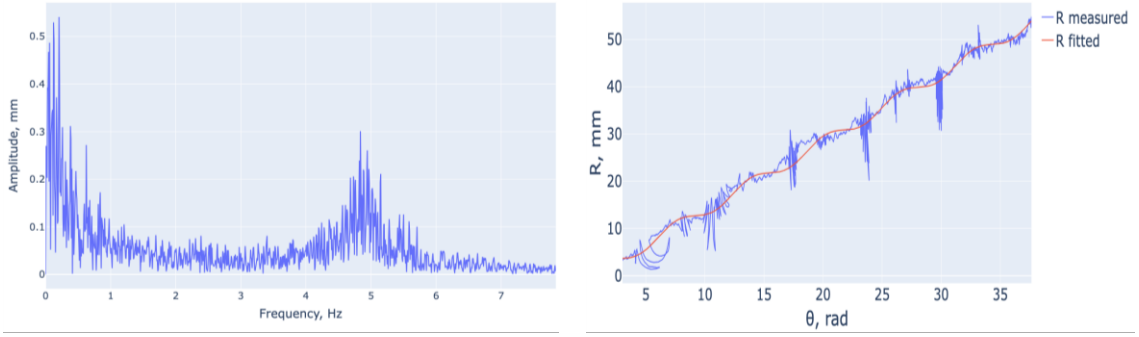
This ΔR isolates involuntary oscillations from the intended drawing path. All EEG channels were normalized by their maximum absolute value; NaN and infinite values were removed before cross-correlation analysis.

For reference, ΔR underwent frequency analysis using the Fast Fourier Transform (FFT). Peaks at 4–6 Hz are typically associated with Parkinson's disease tremor, while ~6–10 Hz suggests essential tremor according to established literature [12, 14]. In our dataset, PD cases without medication showed frequencies consistent with this range, whereas other tremor types — including extrapyramidal tremor of unspecified etiology and post-encephalitic choreiform hyperkinesia — exhibited either no dominant peak or low-frequency oscillations outside the classical PD/ET bands. Although useful for characterizing tremor type, frequency analysis in this study served as a baseline feature, while the novelty lies in the subsequent cross-correlation analysis.



a b

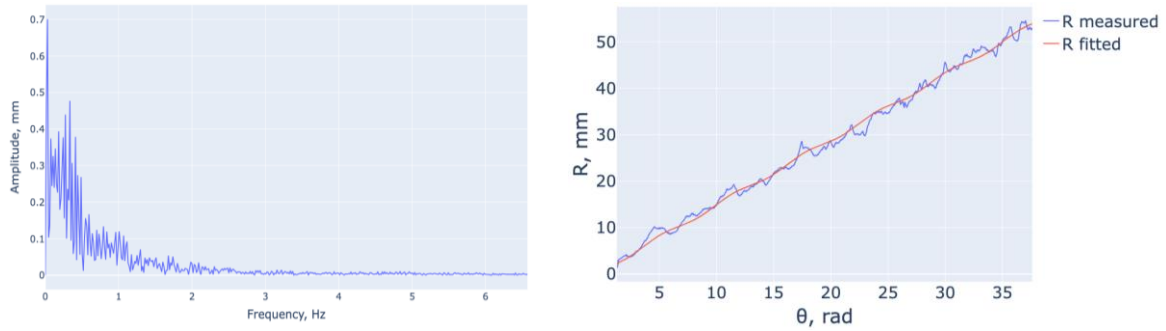
Figure 2. Patient 1 without medication: frequency spectrum of ΔR with a clear peak in the 4–6 Hz tremor band – a; measured radial trajectory vs. fitted spiral, showing larger deviations (ΔR) due to tremor – b



a b

Figure 3. Patient 2 without medication: frequency spectrum of ΔR with a clear peak in the 4–6 Hz tremor band – a; measured radial trajectory vs. fitted spiral, showing larger deviations (ΔR) due to tremor – b

Compared to the medicated state, the presence of a dominant 4–6 Hz peak and higher ΔR amplitude indicates active Parkinsonian tremor.



a b

Figure 4. Patient 1 under medication: frequency spectrum of ΔR without a peak in the 4–6 Hz tremor band – a; measured radial trajectory vs. fitted spiral, where their difference defines ΔR – b

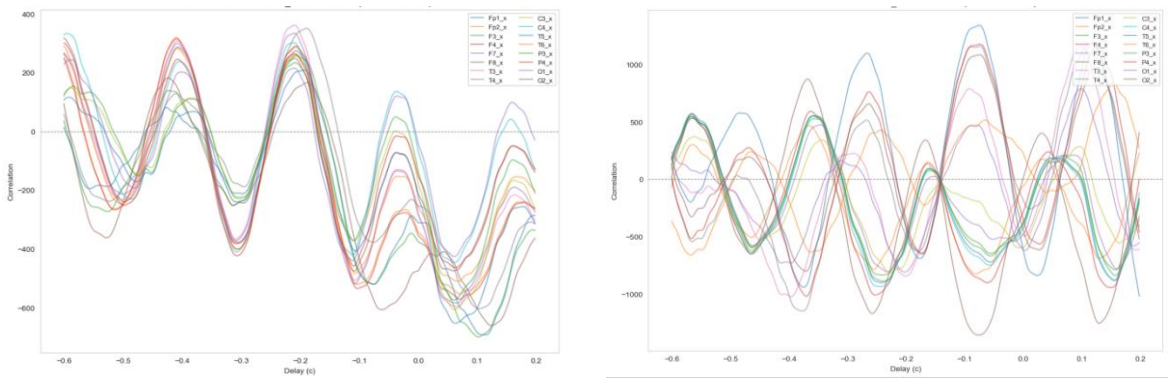
This representation illustrates how ΔR is derived as the deviation between the actual and fitted spiral, and how frequency analysis of ΔR confirms the absence of pathological tremor oscillations under medication.

The cross-correlation between the ΔR(t) signal and the signal of a single EEG channel $e_i(t)$ is defined as:

$$\mathrm{XCorr}_{\Delta R, e_i}(\tau) = \sum_t \Delta R(t) \cdot e_i(t+\tau) \tag{3}$$

where:
τ – time shift (lag),
$\Delta R(t)$ – time series of radial deviations, defined as the difference between the actual radius and the smoothed (model-fitted) radius of the drawing trajectory,
$e_i(t)$ – EEG signal from a specific channel.

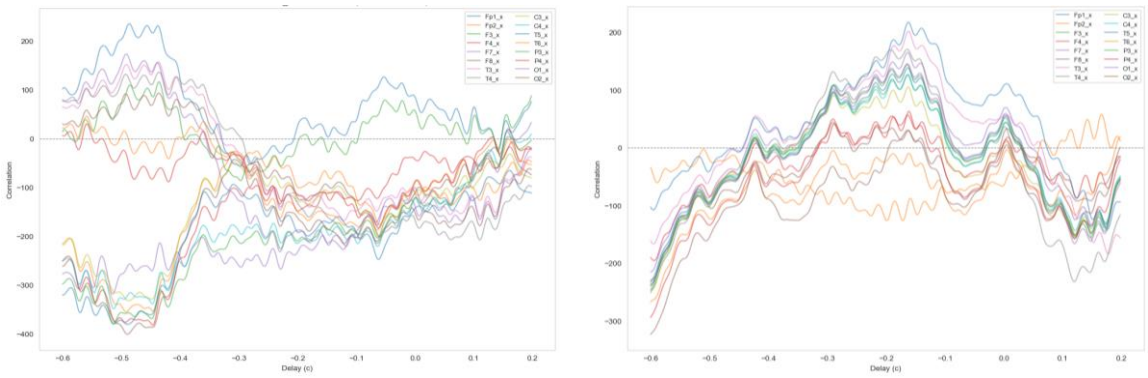
This produced a cross-correlation curve for each channel, capturing both the strength and temporal offset of brain–motor coupling.



a b

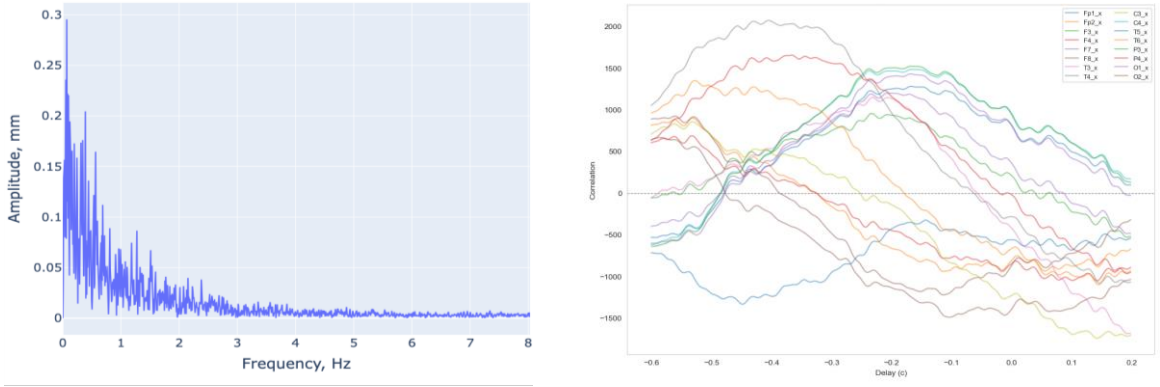
Figure 5. Cross-correlation between ΔR and EEGs (–600 to +200 ms) under active tremor: P1 unmedicated – b; P2 unmedicated – c

The negative lag range in the cross-correlation indicates that EEG activity precedes tremor fluctuations (ΔR), reflecting cortical processes that may drive motor oscillations.



a b

Figure 6. Cross-correlation between ΔR and EEGs (–600 to +200 ms) without tremor: P1 medicated – a; P3 medicated – b



a b

Figure 7. Patient 4 (Extrapyramidal tremor, unspecified etiology): cross-correlation between ΔR and EEGs (–600 to +200 ms) spectral analysis shows no clear 4–6 Hz peak, only low-frequency components – a; cross-correlation curves resemble those of patients without tremor – b

This suggests that the tremor in this patient may arise from mechanisms different from typical Parkinsonian tremor, where strong 4–6 Hz oscillations and synchronized cross-correlation patterns are usually observed.

During visual inspection of the cross-correlation curves, a clear difference was observed between conditions with and without tremor. In the tremor state, multiple EEG channels exhibited highly similar oscillatory profiles, often with synchronized peaks, which can be interpreted as resonance-like coordinated activity across distributed cortical regions. In contrast, under pharmacological suppression of tremor the cross-correlation curves appeared more irregular, with channels showing independent and unsynchronized patterns. To capture this difference quantitatively, a sinusoidality index (SI) was introduced, providing a single measure of the global sinusoidal tendency of cortical synchrony.

For each EEG channel e_i the index was calculated as

$$SI_i = 1 - H_{[3,7]}(\mathrm{XCorr}_{\Delta R, e_i}), \quad (4)$$

where $\mathrm{XCorr}_{\Delta R, e_i}$ denotes the cross-correlation curve between the radial deviation signal ΔR and the EEG channel e_i.

The term $H_{[3,7]}$ represents the normalized spectral entropy of the curve, computed only within the frequency band of 3–7 Hz. This restricted band was chosen because pathological tremor in Parkinson's disease typically exhibits peaks around 4–6 Hz, and the slightly wider window (3–7 Hz) ensures that inter-patient variability and noise are adequately captured while avoiding irrelevant frequencies.

This measure reflects the degree to which the curve approximates a pure sinusoid, with lower entropy corresponding to a stronger sinusoidal tendency.

The overall index for a patient was obtained by averaging across all EEG channels:

$$SI_{avg} = \frac{1}{N}\sum_{i=1}^{N} SI_i, \quad (5)$$

where N is the number of EEG channels.

This formulation ensures that the SI reflects how strongly the energy of cross-correlation curves is concentrated within the tremor band, with higher values indicating resonance-like sinusoidal synchrony across cortical regions.

The resulting scalar value characterizes the global sinusoidal tendency of cortical synchrony associated with tremor.

Table 1

Patient conditions. Tremor frequency (3–7 Hz range) and Sinusoidality Index (SI) across conditions

Patient	Condition	Tremor Frequency (Hz)	Sinusoidality Index (SI, repeated measurements)
P1	PD, no medication	4.5–5.8	0.215, 0.147
P1-med	PD, medicated	None/weak	0.061, 0.067, 0.095
P2	PD, no medication	4.2–5.2	0.400, 0.281, 0.251
P3	PD, medicated	None/weak	0.065, 0.061, 0.050
P4	Extrapyramidal tremor, unspecified etiology	No dominant peak (low-frequency irregularities)	0.120, 0.098, 0.104
P5	Post-encephalitic choreiform hyperkinesia	0.2–1.0 (low-frequency oscillations)	0.129, 0.133, 0.060

During active tremor (P1 without medication), cross-correlation curves from multiple EEG channels showed highly similar shapes and synchronized peaks, resulting in elevated Sinusoidality Index (SI) values across repeated measurements (0.215, 0.147). In another unmedicated PD case (P2), the tremor frequency was 4.2–5.2 Hz, and SI values from three recording sessions reached 0.400, 0.281 and 0.251, indicating very strong cortical synchrony. When tremor was suppressed pharmacologically (P1-med), cross-correlation curves lost their alignment, producing lower SI values in repeated recordings (0.061, 0.067, 0.095). A similar pattern was observed for medicated PD in P3, where no clear tremor frequency was detected and SI dropped to 0.065, 0.061 and 0.050. In the case of extrapyramidal tremor of unspecified etiology (P4), SI values across three measurements were low (0.120, 0.098, 0.104), reflecting partial synchrony. Despite the slow oscillatory pattern (0.2–1 Hz) in post-encephalitic choreiform hyperkinesia (P5), SI remained relatively high across sessions (0.129, 0.133, 0.060), indicating strong cortical synchrony.

These results indicate that Sinusoidality Index (SI), as a single interpretable metric, complements spectral ΔR analysis by reflecting network-level cortical dynamics associated with tremor. Its non-invasive, reproducible nature and clear visual interpretability make it suitable for clinical use and for integration into automated classification systems.

3. CONCLUSIONS AND FUTURE WORK

This study presents an algorithmic framework for tremor assessment that integrates graphomotor and neurophysiological data into a single, interpretable analysis pipeline. The core novelty lies in combining radial deviation analysis (ΔR) from spiral drawing with cross-correlation between ΔR and multiple EEG channels, and in introducing the Sinusoidality Index (SI) to quantify the global sinusoidal tendency of cortical synchrony associated with tremor.

The results across six recording conditions indicate that SI effectively differentiates between active PD tremor, pharmacologically compensated tremor, and certain non-PD tremor types. High SI values (≈0.15–0.40) were consistently observed during active PD tremor (P1, P2) and also in the post-encephalitic choreiform hyperkinesia case (P5) despite its low-frequency nature (0.2–1 Hz). Low SI values (≈0.05–0.10) were characteristic of pharmacologically suppressed PD tremor (P1-med, P3) and extrapyramidal tremor of unspecified etiology (P4). These findings support the hypothesis that pathological tremor – regardless of frequency – can involve a resonance-like, coordinated activation pattern across distributed cortical regions, which becomes desynchronized when tremor subsides or originates from less synchronized neural generators.

Compared with purely spectral ΔR analysis [16] (see also [19]), which captures the presence and frequency of motor oscillations, cross-correlation analysis provides a direct view of the temporal relationship between EEG activity and tremor dynamics. Building on this foundation, the Sinusoidality Index (SI) offers a complementary, scalar measure of the sinusoidal structure in cross-correlation curves, reflecting network-level brain dynamics. This dual view – oscillatory motor features revealed by cross-correlation and cortical synchrony quantified by SI – offers a richer diagnostic picture and a potential basis for more precise tremor classification.

From a practical standpoint, the method is non-invasive, relies on affordable hardware (graphics tablet and EEG), and produces visual outputs (cross-correlation overlays, sinusoidality profiles) that are intuitive for clinicians. It is reproducible across sessions and can be adapted for rule-based diagnostic tools as well as hybrid approaches.

Potential avenues for further research in this field include:

1. Expanding participant cohorts to include healthy controls, early-stage PD, and other tremor syndromes such as dystonic or cerebellar tremor.
2. Automating the analysis pipeline for real-time or near-real-time monitoring, including portable and cloud-based solutions.
3. Extending the cross-correlation framework to sliding-window analyses, enabling detection of transient changes in brain-motor coupling.
4. Exploring integration with advanced pattern-recognition methods, while retaining SI as an interpretable feature.
5. Longitudinal validation to assess sensitivity to treatment effects and disease progression.

In summary, combining ΔR-based motor analysis with EEG-derived synchrony metrics provides an objective, explainable, and scalable approach to tremor assessment. Its simplicity, interpretability, and adaptability suggest strong potential for future diagnostic systems in both clinical and remote healthcare contexts.

The study's results contribute to the development of high-performance software tools for multimodal signal analysis and pattern recognition, reinforcing the applied dimension of computer science and software engineering in neurodiagnostic systems.

References

1. Alrawis M., Al-Ahmadi S., Mohammad F. (2024) Bridging modalities: A multimodal machine learning approach for Parkinson's disease diagnosis using EEG and MRI data. Appl. Sci, vol. 14, no. 9, art. 3883. https://doi.org/10.3390/app14093883
2. Jain S., Srivastava R. (2024) Multi-modality NDE fusion using encoder–decoder networks for identify multiple neurological disorders from EEG signals. Technol. Health Care, vol. 1, art. 09287329241291334. https://doi.org/10.1177/09287329241291334
3. Tang L., Hu Q., Wang X., Liu L., Zheng H., Yu W., Song C. (2024) A multimodal fusion network based on a cross-attention mechanism for the classification of Parkinsonian tremor and essential tremor. Sci. Rep, vol. 14, art. 28050. https://doi.org/10.1038/s41598-024-79111-w
4. Guo Y., Huang D., Zhang W., Wang L., Li Y., Olmo G., Chan P. (2022) High-accuracy wearable detection of freezing of gait in Parkinson's disease based on pseudo-multimodal features. Comput. Biol. Med, vol. 146, art. 105629. https://doi.org/10.1016/j.compbiomed.2022.105629
5. Ma C., Ma Y., Pan L., Li X., Yin C., Zong R., Zhang Z. (2023) Automatic diagnosis of multi-task in essential tremor: Dynamic handwriting analysis using multi-modal fusion neural network. Future Gener. Comput. Syst, vol. 145, pp. 429–441. https://doi.org/10.1016/j.future.2023.03.033
6. Raj K. D., Lal G. J., Gopalakrishnan E. A., Sowmya V., Orozco-Arroyave J. R. (2024) A visibility graph approach for multi-stage classification of Parkinson's disease using multimodal data. IEEE Access, vol. 12, pp. 87077–87096. https://doi.org/10.1109/ACCESS.2024.3416444
7. Miah A. S. M., Suzuki T., Shin J. (2025) A methodological and structural review of Parkinson's disease detection across diverse data modalities. IEEE Access, vol. 13, pp. 98931–98975. https://doi.org/10.1109/ACCESS.2025.3575023
8. Murtaza G., Hammoud M., Somov A. (2025) Multi-modal feature set-based detection of freezing of gait in Parkinson's disease patients using SVM. IEEE Access, vol. 13, pp. 114798–114811. https://doi.org/10.1109/ACCESS.2025.3585099
9. Skaramagkas V., Pentari A., Kefalopoulou Z., Tsiknakis M. (2023) Multi-modal deep learning diagnosis of Parkinson's disease – A systematic review. IEEE Trans. Neural Syst. Rehabil. Eng, vol. 31, pp. 2399–2423. https://doi.org/10.1109/TNSRE.2023.3277749
10. Dhivyaa C. R., Nithya K., Anbukkarasi S. (2024) Enhancing Parkinson's disease detection and diagnosis: A survey of integrative approaches across diverse modalities. IEEE Access, vol. 12, pp. 158999–159024. https://doi.org/10.1109/ACCESS.2024.3487001
11. Farashi S., Sarihi A., Ramezani M., Kashani H. (2023) Parkinson's disease tremor prediction using EEG data analysis – A preliminary and feasibility study. BMC Neurol, vol. 23, no. 1, p. 420. https://doi.org/10.1186/s12883-023-03468-0
12. Yu N. Y., Van Gemmert A. W. A., Chang S. H. (2017) Characterization of graphomotor functions in individuals with Parkinson's disease and essential tremor. Behav. Res. Methods, vol. 49, no. 3, pp. 913–922. https://doi.org/10.3758/s13428-016-0752-y
13. Brambilla C., Pirovano I., Mira R. M., Rizzo G., Scano A., Mastropietro A. (2021) Combined use of EMG and EEG techniques for neuromotor assessment in rehabilitative applications: A systematic review. Sensors, vol. 21, no. 21, Art. 7014. https://doi.org/10.3390/s21217014
14. Zhang X., Chen H., Tao L., Zhang X., Wang H., He W., Fang W. (2022) Combined multivariate pattern analysis with frequency-dependent intrinsic brain activity to identify essential tremor. Neurosci. Lett, vol. 776, Art. 136566. https://doi.org/10.1016/j.neulet.2022.136566
15. Chyniak O., Dubenko O., Potapov O., Shulha A., Kotsiuba A. (2023) Parkinson's disease - an overview of modern treatment methods. EUMJ, vol. 11, no. 1, pp. 1–13. [in Ukrainian].
16. Petryk M., Bishchak D., Bachynskyi M., Brevus V., Chyzh V., Mykhalyk D. (2024) Analysis of involuntary movements of patients with tremor symptoms under the influence of cognitive influences. Applied issues of mathematical modeling, vol. 7, no. 2, pp. 150–165. [in Ukrainian].
17. Osiichuk I., Brevus V., Bishchak D., Mashtaliar Y., Mudryk I. (2024) Leveraging graphics tablet and JPen library to detect essential tremor. CEUR Workshop Proc,vol. 3742, pp. 63–69.
18. Pastukh O., Yatsyshyn V. (2023) Brain-computer interaction neurointerface based on artificial intelligence and its parallel programming using high-performance calculation on cluster mobile devices. Visnyk TNTU, no. 4 (112), pp. 26–31. https://doi.org/10.33108/visnyk_tntu2023.04.026
19. Andersen R. A. (2019) From thought to action: The brain–machine interface in posterior parietal cortex. Proc. Natl. Acad. Sci, vol. 116, no. 52, pp. 26274–26279. https://doi.org/10.1073/pnas.1902276116

УДК 616.858-008.6:616.8-073.97:616.8-009.3

АЛГОРИТМІЧНИЙ ПІДХІД ДО КЛАСИФІКАЦІЇ ТРЕМОРУ ЗА EEG І ГРАФОМОТОРНИМИ СИГНАЛАМИ

Дмитро Біщак; Михайло Петрик

Тернопільський національний технічний університет імені Івана Пулюя, Тернопіль, Україна

Резюме. *Представлено алгоритмічний підхід до класифікації та диференційної діагностики тремору, що ґрунтується на мультимодальному аналізі електроенцефалографічних (EEG) сигналів та графомоторної активності, зареєстрованої під час виконання пацієнтами завдання малювання спіралі на графічному планшеті зі стілусом. Для кількісного оцінювання моторних відхилень застосовано показник ΔR – різницю між реальною траєкторією руху стілуса та її згладженою (референтною) версією, отриманою шляхом параметричної криволінійної апроксимації. EEG-сигнали синхронізовано з графомоторними даними та піддано попередньому опрацюванню, включно з нормалізацією та інтерполяцією. Для подальшого аналізу використано всі наявні канали EEG з метою повного відображення просторово-часових патернів мозкової активності. Основу методу становить аналіз крос-кореляції між ΔR та кожним каналом EEG, що дозволяє виявляти просторово-часові патерни мозкової активності, асоційовані з тремором, а також досліджувати ступінь їхньої синхронності. Запропоновано індекс синусоподібності (SI), який обчислюється для крос-кореляційних кривих та виступає інтегральним показником глобальної синусоподібної тенденції кортикальної синхронізації у різних клінічних станах. Експериментальні дослідження проведено на даних, отриманих від пацієнтів з різним клінічним статусом, включаючи хворобу Паркінсона у стані медикаментозної компенсації та без неї, а також тремор невстановленого генезу. Результати показали, що виражений тремор супроводжується підвищеною синхронізацією між каналами EEG, тоді як у стані компенсації або зниження симптомів активність каналів є більш незалежною. Запропонований підхід має значну діагностичну цінність, оскільки поєднує кількісні обчислювальні методи з можливістю адаптації під індивідуальні особливості пацієнта, і може бути використаний як основа для розроблення портативних або хмарних систем автоматизованого аналізу та моніторингу тремору, що розширює можливості телемедицини та персоналізованої нейродіагностики. Запропонований алгоритмічний підхід інтегрує сучасні методи інженерії програмного забезпечення для мультимодальної синхронізації сигналів, числового аналізу та виділення ознак, що являє прикладне вирішення на перетині опрацювання біомедичних даних і комп'ютерних наук.*

Ключові слова: *тремор, електроенцефалографія, електроенцефалографічний сигнал, ЕЕГ, графомоторні сигнали, ΔR, хвороба Паркінсона, частотний аналіз, крос-кореляція, класифікація, програмне забезпечення, комп'ютерна діагностика, медична діагностика, інформаційна система, набори даних, часові ряди, алгоритм, адаптивне програмне забезпечення, адаптивна система, цифрова платформа, обробка сигналів, оцінювання, нормалізація, автоматизація.*

https://doi.org/10.33108/visnyk_tntu2025.03.035 *Отримано 10.07.2025*