Pursuit Regularity Index for Parkinson's Disease Detection via videonystagmography

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***Abstract*—We introduce a novel indicator for the automatic detection of Parkinson's disease, a neurodegenerative disorder characterized by motor impairments, including abnormal eye movements. This study, conducted in the context of videonystagmography (VNG), investigates the Pursuit Regularity Index (PRI), which quantifies the spectral sparsity of pupil motion during target tracking. We assess the potential of PRI to improve classification accuracy when combined with other VNG-derived features. Using a proprietary dataset collected at Razi University Hospital in Tunisia, our results demonstrate that integrating PRI into machine learning models significantly enhances the accuracy and reliability of PD detection.**

***Index Terms*—Parkinson's Disease, eye movement, videonystagmography, feature extraction, classification.**

I. Introduction

Parkinson's disease (PD) is a progressive neurodegenerative disorder that lacks reliable biomarkers. Its diagnosis traditionally relies on the clinical assessment of symptoms such as tremor, rigidity, akinesia, and postural instability [1]. These assessments are often complemented by additional tests, such as brain imaging for differential diagnosis [2]. The neurodegenerative process in PD is often preceded by a prodromal phase that can last several years before the onset of the first motor symptoms. As a result, a diagnosis based solely on clinical evaluation may be insufficient, particularly in the very early stages of the disease, when motor signs are subtle or absent, and non-motor symptoms may be nonspecific.

Currently, advances in Machine Learning (ML) techniques are opening new perspectives in the diagnosis of neurological disorders, including PD [3]. ML algorithms use various types of data for PD diagnosis, including neuroimaging [4], hand movement [5] and voice recordings [6]. Electroencephalography (EEG) can identify specific brain wave alterations in patients with PD. In [7], the authors demonstrated that applying signal processing techniques and ML algorithms to resting-state EEG data can distinguish PD patients from healthy individuals with 97.5% accuracy. Similarly, in [8], handwriting features analyzed using neural networks enabled PD detection with over 90% accuracy, highlighting its diagnostic potential.

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While biological signals are commonly used for PD diagnosis, eye movement (EM) analysis remains relatively underexplored, despite its potential to provide reliable and non-invasive indicators for PD detection. Indeed, studies have shown that ocular alterations can be detected even before clinical motor symptoms appear [9], making them promising prodromal biomarkers for PD. A clinical study [10] conducted on 30 untreated PD patients and 31 healthy controls (HC) revealed several EM abnormalities in PD patients. These included reduced convergence amplitudes and a decreased blink rate compared to HC. PD has also been investigated through the analysis of pro-saccades and anti-saccades in EM tests [11], [12]. Pro-saccades require participants to shift their gaze toward a peripheral stimulus, while anti- saccades involve looking in the opposite direction. These tests can reveal abnormalities in pupillary responses, offering valuable insights into the neurological alterations associated with PD.

The integration of non-invasive eye tracking technology, such as video eye tracker and videonystagmography (VNG), has advanced the understanding of EM disorders, revealing their connection to underlying neurophysiological mechanisms [13]. Additionally, these technologies have facilitated the application of advanced ML algorithms to recorded EM data, significantly improving the accuracy of the diagnosis [14]. For instance, in [15], authors classified saccadic EM collected via VNG from 100 subjects (PD and HC) and achieved an accuracy of 84%. In another study [16], researchers analyzed eye-tracking data from pro/anti-saccade video recordings of 121 patients with various atypical PD syndromes and 106 HC, obtaining an accuracy of 83%. Additionally, [17] analyzed the raw waveforms of saccade time series from 127 participants to distinguish PD from PSP and HC, achieving an accuracy of 64%. Although these recent findings confirm that automated approaches offer objective quantification of oculomotor deficits, promising more reliable and reproducible diagnostic tools, these methods often rely on a limited number of participants at varying disease stages. Additionally, the diversity of EM tasks used in studies affects performance assessment, further complicating the interpretation of oculomotor dysfunctions in PD [18].

In this paper, we introduce the Pursuit Regularity Index (PRI) as a novel feature for PD detection. It quantifies the

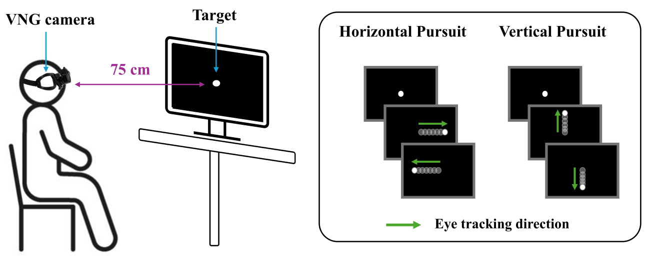

Fig. 1: Eye movement acquisition protocol.

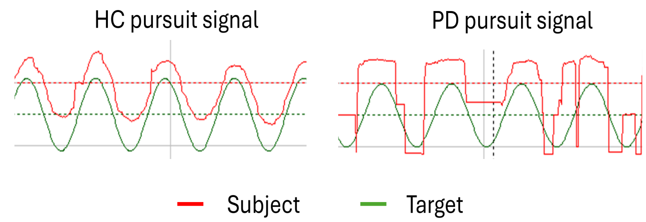

Fig. 2: Example of a VNG pursuit signal from a Healthy Control (HC) and a patient with Parkinson's disease (PD).

spectral sparsity of pupil motion while tracking a sinusoidally varying target, offering a precise assessment of smooth pursuit. While smooth pursuit oculomotor disorders have been studied, the use of sparsity measures such as PRI to quantify these aspects remains unexplored. To investigate this, we analyzed EM—including pro/anti-saccades and smooth pursuit—recorded by VNG. Data collection took place at Razi University Hospital in La Manouba, Tunisia, under the supervision of neurologists, ensuring both reliability and clinical relevance. For ML analysis, we tested multiple classifiers and employed a robust cross-validation method to ensure an unbiased evaluation.

The remainder of the paper is structured as follows: Section II describes the database, feature extraction process, and an overview of the proposed methods. Section III presents the experimental findings, while Section IV discusses the main results and provides perspectives for future work.

II. Methodology

A cross-sectional study was conducted at the Department of Neurology, Clinical Investigation Centre Neurosciences and Mental Health, Razi University Hospital, Tunisia, between November 2023 and April 2024. The study population consisted of 42 PD patients and 44 healthy controls (I). Inclusion criteria for PD patients required a confirmed diagnosis of PD. Exclusion criteria included the presence of cognitive impairments that could interfere with oculomotor assessment, as well as any conditions or treatments known to influence oculomotor function (e.g., diabetes mellitus, psychotropic medications [19]). All HC underwent a comprehensive neurological examination to exclude any neurological abnormalities or vestibular disorders that might introduce artifacts into eye movement recordings. Motor disability was assessed using part III of the Unified PD Rating Scale (UPDRS III). All participants provided informed consent in accordance with the study protocol. All acquisitions were conducted with the approval of the Razi Hospital Ethics Committee (approval number: P2021-005).

A. Data acquisition and processing

1) Experimental protocol: Eye movements were recorded and analyzed using a VNG system (Synapsys™, Goggles Flex; VNS3X monocular camera; and Ulmer software), a non-invasive and reliable method to assess oculomotor functions based on stimulated eye movements (EM). This technique measures key parameters from specific EM tasks—saccadic and smooth pursuit in this study—such as latency, speed, and precision, providing valuable insights into the neural circuits involved in eye movement control.
Participants were asked to follow a white circular light stimulus displayed on a black screen, with their eyes, without making head movements, as illustrated in Fig. 1. They were seated 75 cm from a 42-inch projection screen in a quiet, dimly lit room. The camera was positioned on the right eye by default, unless the left one was identified as more suitable for recording. Each EM task lasted approximately 60 seconds and was repeated twice. Prior to each eye examination, participants received clear instructions and a practical demonstration to ensure their understanding. Throughout the sessions, regular verbal encouragement was provided to maintain their attention.

2) Oculomotor Assessments: Saccadic EM tasks are categorized into two types: reflexive and voluntary. Reflexive saccades, also known as visually guided saccades, are rapid eye movements in which participants must quickly shift their gaze to a target stimulus as soon as it appears. In contrast, voluntary saccades, or anti-saccades, require participants to rapidly direct their gaze in the opposite direction of the stimulus [20]. The anti-saccade task is commonly used to assess voluntary eye movements and the ability to inhibit reflexive responses. In addition, the smooth pursuit task involves a slow, continuous, and voluntary tracking of a moving stimulus, with the stimulus's angular amplitude following a sinusoidal trajectory. This task requires precise coordination between EM and target motion. Oculomotor disorders are more pronounced in voluntary saccades than in reflexive saccades during the early stages of PD, manifesting as increased latency, reduced precision, and impaired inhibition of reflexive saccades during anti-saccadic tasks [21]. Additionally, PD patients exhibit altered pursuit gain and impaired convergence ability [22]. These abnormalities represent potential biomarkers for disease

TABLE I: Clinical characteristics of participants.

	HC	PD
Number of subjects	44	42
Gender (female:male)	29:15	24:18
Mean age ± SD (years)	56.6 ± 11.1	67.2 ± 8.61

progression and associated cognitive deficits [23].

EM were recorded for approximately one minute, with pro-saccades and anti-saccades measured in the horizontal plane, while pursuit movements were recorded in both horizontal and vertical directions. Saccadic EM were assessed using Freyss square signals with a pseudo-random period and an angular amplitude of $\pm 20°$, while pursuit was assessed at a frequency of 0.3 Hz with an angular amplitude of $\pm 35°$.

B. Feature extraction

The VNG system, equipped with Ulmer software, instantly extracts the eye movement signal from the video recording and displays it as a time series on the VNG command screen, alongside the target signal (amplitude in degrees vs. time). An example of a VNG tracking signal is shown in Fig. 2. The time series from EM recordings are then processed by the VNG software to compute a set of 16 oculomotor indicators, including latency, velocity, precision, and gain (Table II). These measures provide valuable insights for clinicians to quantify oculomotor abnormalities associated with neurodegenerative diseases and aid in differentiating Parkinsonian syndromes [24]. However, these VNG measures are only displayed on the command screen and are not automatically exported with the raw EM signals, limiting their direct integration in ML models. To overcome this limitation, we manually exported the 16 metrics in order to integrate them into the ML modeling process.

The use of ocular indicators in the automatic detection of PD remains understudied and insufficiently explored. One major challenge is the lack of a publicly available and standardized methodology for calculating VNG-derived measures, making their integration into automated classification approaches difficult. Moreover, existing studies have primarily focused on the clinical analysis of VNG signals without fully exploiting their quantitative potential. In this work, we propose computing a novel measure directly from the raw VNG pursuit signals to improve the accuracy and reliability of automatic PD detection, when combined with VNG-provided metrics.

C. Pursuit Regularity Index (PRI)

We propose a quantitative indicator to assess the regularity of eye movements during the pursuit task: the Pursuit Regularity Index (PRI). In healthy controls, pursuit movements are generally smooth and regular, resulting in a sinusoidally varying signal along the time axis (see Fig. 2). In contrast, PD pursuit movements exhibit irregularities and fluctuations, reflecting impairments in oculomotor control. In the frequency domain, this corresponds to a sparser spectrum for HC compared to PD. The closer the ocular signal is to a sine wave, the sparser its spectrum. The regularity of eye motion over time can be quantified by its spectral sparsity, measured using the Hoyer index [25], which is referred to here as the PRI, and is defined as:

TABLE II: Description of VNG measures [20].

VNG Measure	Definition
Latency (ms)	Time delay between the onset of the stimulus movement and the start of the eye movement
Velocity (°/s)	Computed from time series of gaze position data by taking the 1^{st} derivative
Precision (%)	Ratio of EM amplitude (in°) to target amplitude
Gain	Ratio of eye velocity to target velocity

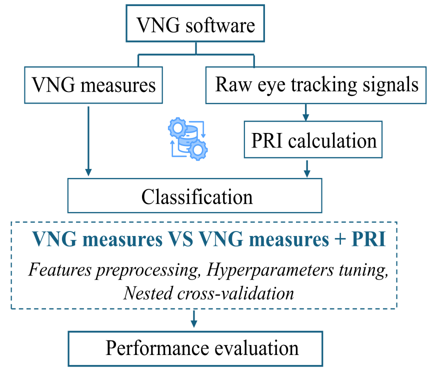

Fig. 3: Proposed VNG-based classification flowchart.

$$\mathrm{PRI} = \frac{\sqrt{N} - \frac{\|X\|_1}{\|X\|_2}}{\sqrt{N} - 1},$$

where $\|X\|_1$ and $\|X\|_2$ are the L1 and L2 norms of the Fourier transform X of the EM signal, respectively, with N the number of frequency samples. A PRI close to 1 indicates a signal that is sparse in the frequency domain, while a PRI near 0 suggests a more spread spectrum, and hence a noise-like signal. The HC pursuit signal, which corresponds to a slightly noisy sine wave, will have a PRI close to 1, though slightly lower than that of the target. In contrast, a PD signal, characterized by greater variability, will have a lower PRI, tending towards 0. This principle motivates the use of PRI as a new indicator for detecting disturbances. However, this index captures only the signal's regularity and should be combined with other VNG measures, such as speed or gain, to provide a more comprehensive assessment.

D. Proposed classification framework

Fig. 3 illustrates the automatic eye tracking-based classification implemented in this study. Both the target and subject raw signals are exported from the VNG software. The PRI is then calculated from these raw tracking signals for each participant. Classification is subsequently determined based on both the PRI and the VNG-provided metrics.

To build an unbiased model, nested k-fold cross-validation [26] was employed to prevent potential overfitting. Despite the limited dataset, only one of the two VNG measurements recorded per task and per subject was selected in order to ensure consistency and avoid redundancy in the classification process [27]. Feature preprocessing was applied

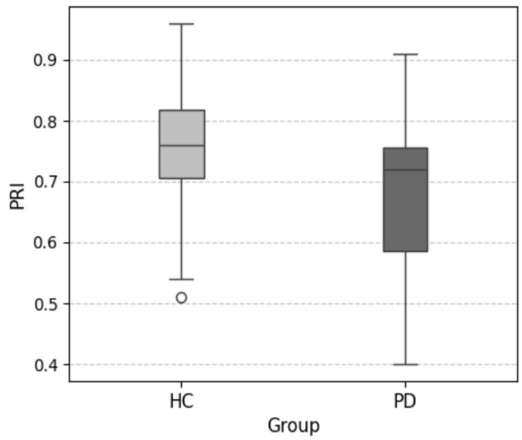

Fig. 4: Comparison of PRI distribution for horizontal pursuit.

to the training set in each iteration of the outer fold cross-validation. Normalization was performed using MinMaxScaler, with the minimum and maximum values of the features computed solely from the training set, ensuring that the test set did not influence the training process. These parameters were then used to normalize both the training and test sets. We trained several supervised ML models: k-Nearest Neighbor (KNN), Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), and Gradient Boosting (GB). Classifiers' performance was evaluated using standard metrics, such as precision, recall, specificity, and F1-score.

III. Results and discussion

A. Ocular data analysis

To assess the normality of the data, we used the Shapiro-Wilk test, which is suitable for small sample sizes [28]. The results presented in Table III indicate that some characteristics, such as pro-saccade velocity and right anti-saccade precision, do not follow a normal distribution (p-value$<$0.05). Consequently, we applied the Mann-Whitney test for these features, while the t-test was used for features showing normality. The results revealed that only two features—PRI of horizontal pursuit and right anti-saccade precision—were statistically significant, with p-values of 0.024 and 0.033, respectively, suggesting potential differences between the studied groups. The statistical significance of PRI of horizontal pursuit highlights its potential as an effective biomarker for distinguishing PD from HC. In contrast, other ocular measures did not show significant differences.

B. PRI descriptive analysis

Statistical analysis of the PRI in horizontal eye tracking reveals a significant difference between the two groups, with a p-value of 0.016. This analysis is further supported by a descriptive approach using boxplots, as shown in Fig. 4. Comparing the PRI distributions in horizontal pursuit, we observe that the PD group exhibits a higher median PRI than the HC group, along with greater dispersion. This suggests increased irregularity in their horizontal pursuit movements, reflecting impairment in the control of smooth eye tracking. These findings align with previous studies that link PD to oculomotor deficits, which affect gaze stability [22].

C. Classification results

As shown in Table IV, all the considered ML algorithms perform poorly when relying solely on VNG-provided metrics. However, integrating PRI data as an additional PD-related EM indicator significantly enhances the performance of all classifiers, leading to notable improvements in both accuracy and F1-score. Among the tested models, GB achieves the highest accuracy after PRI integration (72.09%), followed closely by KNN at 70.84%. As for the F1-score, it reflects the trade-off between precision and recall and is used to assess the models' ability to correctly detect both classes, particularly in a potentially unbalanced dataset. Employing only VNG data, the F1-scores remain modest, ranging from 26.29% (SVM) to 54.37% (KNN), suggesting the models' difficulty in generalizing their results. However, incorporating the PRI index results in a significant improvement, with F1-scores ranging from 55.99% (DT) to 64.55% (GB). This improvement indicates that PRI measures provide complementary discriminative information to the VNG data, thus improving the quality of predictions. These results support previous statistical interpretations and demonstrate that PRI is a valuable complement to VNG-provided metrics. Moreover, they confirm that PRI is a reliable indicator of EM control impairments during pursuit tasks.

It is important to note that our primary objective was not to achieve the highest possible classification performance but rather to highlight the added value of PRI as a novel metric

TABLE III: Statistical significance of different EM indicators.

Feature	VNG task	Normality	p-value
PRI	H. Pursuit	Normal	**0.024**
PRI	V. Pursuit	Normal	0.102
Right gain	H. Pursuit	Normal	0.342
Left gain	H. Pursuit	Normal	0.368
Upper gain	V. Pursuit	Normal	0.51
Lower gain	V. Pursuit	Normal	0.847
Right latency	Saccade	Normal	0.372
Left latency	Saccade	Normal	0.53
Right speed	Saccade	Non-Normal	0.633
Left speed	Saccade	Non-Normal	0.29
Right precision	Saccade	Non-Normal	0.458
Left precision	Saccade	Non-Normal	0.872
Right latency	Antisaccade	Normal	0.715
Left latency	Antisaccade	Normal	0.309
Right speed	Antisaccade	Non-Normal	0.128
Left speed	Antisaccade	Non-Normal	0.364
Right precision	Antisaccade	Non-Normal	**0.033**
Left precision	Antisaccade	Non-Normal	0.687

TABLE IV: Comparison of classifiers performance (in %)

Classifier	VNG data		VNG data + PRI	
	Accuracy	F1-score	Accuracy	F1-score
KNN	56.99 ± 13.90	54.37	70.84 ± 4.51	58.00
DT	48.16 ± 4.67	43.76	65.76 ± 4.62	55.99
SVM	42.06 ± 7.64	26.29	63.63 ± 10.32	60.43
RF	53.31 ± 11.57	49.76	67.24 ± 5.47	62.43
GB	54.34 ± 6.13	53.37	**72.09 ± 6.24**	**64.55**

for the automatic detection of PD. Further analysis of the VNG-provided metrics revealed that some features exhibit strong correlations, particularly among pro-saccade measures, whereas anti-saccade metrics show relatively low correlation. These findings underline the need for further investigation into feature selection, to refine the set of indicators and retain only the most relevant and discriminative features for PD detection.

IV. Conclusion and Future Directions

In this study, we introduced the Pursuit Regularity Index (PRI) as a novel indicator for the automatic detection of PD. Using a newly collected database of biomedical oculomotor signals recorded via videonystagmography at the Department of Neurology, Clinical Investigation Centre Neurosciences and Mental Health, Razi University Hospital, Tunisia, we demonstrated the added value of PRI in PD classification. Statistical analyses confirmed that PRI provides relevant information that enriches standard VNG-provided measures, leading to a significant improvement in classifier performance. While the obtained classification results do not surpass state-of-the-art approaches, our primary objective was to highlight PRI's potential as a complementary measure in PD eye movement analysis. These findings validate PRI as a reliable indicator of oculomotor regularity and fluidity, offering a new perspective for assessing PD-related deficits.

However, our study has several limitations. First, the relatively small size of the dataset used for analysis may limit the generalizability of the results, highlighting the need for a larger and more diverse sample in future studies. Second, although classifier performance improved with the inclusion of PRI, the results remain moderate, suggesting that additional features could be explored to further enhance the model's performance. A more in-depth statistical analysis of VNG-provided eye movement features could also contribute to this optimization.

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