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Activation of Different Brain Regions in the Resting State in Parkinson's Patients Analyzed by fNIRS

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Abstract:

Despite the difficulties associated with data processing, fNIRS technology shows promise for advancing cognitive studies and Parkinson's disease research through the integration of deep learning techniques. The veracity and dependability of fNIRS data are contingent upon meticulous data collection, robust signal processing, and an acknowledgement of its inferior spatial resolution and restricted penetration depth in comparison to fMRI. The integration of resting and task state analyses using fNIRS provides a detailed insight into Parkinson's disease, elucidating both the intrinsic brain connectivity disruptions and the dynamic responses to cognitive challenges. This enhances the diagnostic and treatment strategies employed in this field. The integration of fNIRS with EEG, motion capture, and advanced data analysis techniques markedly enhances the diagnostic accuracy of Parkinson's disease. This is achieved by revealing distinct brain connectivity states and movement patterns, thereby paving the way for more sophisticated diagnostic and treatment approaches. The effective management of motion artefacts in fNIRS data for Parkinson's disease research is achieved through the utilisation of advanced algorithms, including single-channel MAR, band-pass filtering and PCA. Collectively, these algorithms enhance the signal quality and facilitate the interpretability of brain activity patterns.

Keywords: fNIRS; Parkinson's disease; deep learning techniques; diagnostic accuracy.

1. Introduction

Functional near-infrared spectroscopy (fNIRS) is a non-invasive and safe neuroimaging technique for monitoring brain activity. In comparison to other neuroimaging techniques, such as functional magnetic resonance imaging (fMRI) and electroencephalography/magnetoencephalography (EEG/MEG), fNIRS is a non-invasive and safe method that can be used in conjunction with body movements and is highly por-

table, which makes it an ideal choice for a variety of applications. It is suitable for all possible participant groups, from newborns to the elderly, as well as for a wide range of experimental setups, both indoors and outdoors [1]. Functional near-infrared spectroscopy (fNIRS) measures the concentration of blood oxygen to continuously and non-invasively monitor brain function [2].

fNIRS data acquisition is based on the optical properties of brain tissues and hemodynamic responses. It uses near-infrared light (650-950 nm wavelengths) to penetrate the skull and brain tissues. This light is absorbed differently by oxygenated (HbO) and deoxygenated (HbR) hemoglobin. When a brain region activates, local blood flow increases, changing HbO and HbR concentrations. fNIRS devices emit light from sources on the scalp and detect reflected light using detectors. By measuring light intensity at different wavelengths, fNIRS quantifies changes in HbO and HbR concentrations, indirectly indicating neural activity. Multiple source-detector pairs form channels, providing spatial information about brain activity across different regions with high temporal resolution.

Significant advancements have been made in the development and application of fNIRS technology. For instance, to enhance the spatial resolution of imaging and to derive more efficacious data on brain function, multi-distance probe configurations have been devised and the modified Beer-Lambert law (MBLL) with partial path length (PPL) methodology has been put forth [3]. Furthermore, the utilisation of fNIRS in cognitive developmental studies has been emphasized, particularly in the investigation of mathematical and linguistic abilities [4]. Additionally, fNIRS has been employed in brain-computer interface (BCI) studies to regulate cognitive functions and control neuronal functions in the brain by incorporating fNIRS [2].

Despite these advancements, challenges remain. There are still some issues in fNIRS data processing and signal quality control. It has been demonstrated that research articles utilizing fNIRS exhibit considerable heterogeneity in analytical methodologies and preprocessing procedures. Additionally, these articles frequently lack comprehensive descriptions of the employed methods, which is essential for ensuring the replicability and comparability of results [5]. Moreover, fNIRS signal processing is not standardized and is significantly influenced by experience and manual procedures [6]. Nevertheless, the application of deep learning (DL) techniques has demonstrated rapid and precise performance in fNIRS studies, outperforming traditional machine learning techniques in data processing and classification tasks [7].

Parkinson's disease is the second most prevalent neurodegenerative disease after Alzheimer's disease, affecting approximately 1% of the global population. The disease is characterized by a combination of movement and non-movement disorders. The primary movement disorders associated with Parkinson's disease includes tremors, muscle stiffness, slowed movement, and balance problems. Non-motor disorders, on the other hand, encompass a range of symptoms such as reduced sense of smell, sleep disorders, and depression [8].

The precise etiology of Parkinson's disease remains elusive, although research indicates a potential association with oxidative stress and mitochondrial electron transport chain (ETC) dysfunction. In patients with Parkinson's disease, dopaminergic neurons in the substantia nigra are impaired, which has been linked to defects in the function of the mitochondrial ETC complex I. Furthermore, some studies have identified reduced ETC complex I activity in platelets and brain tissue in patients with Parkinson's disease [9].

Given the significant impact of Parkinson's disease, research efforts have been ramping up. In recent years, research on Parkinson's disease has intensified. For example, the video analysis tool SS-180 has been used to assess a patient's gait and turning ability. This has been shown to be comparable to laboratory standards and to have good reliability and reproducibility [10]. Furthermore, genetic studies on Parkinson's disease are ongoing. For example, the discovery of the PARK8 gene has provided new insights into the genetic background of the disease.

2. Application and details of fNIRS technology in Parkinson's diagnosis

2.1 Accuracy and reliability of functional near-infrared spectroscopy (fNIRS) in the diagnosis of Parkinson's disease

Functional near-infrared spectroscopy (fNIRS) is a non-invasive and relatively safe neuroimaging technique for monitoring brain activity. It is distinguished by low cost and portability, which makes it a promising tool for diagnosing brain diseases such as Parkinson's disease [11]. However, to assess the accuracy and reliability of fNIRS in diagnosing Parkinson's disease, it is essential to consider a number of factors. Firstly, several factors may compromise the quality of data obtained from functional near-infrared spectroscopy (fNIRS). These include alterations in the optical properties of tissues, contamination of biological signals, and modulation of neural activity [12]. These factors have the potential to result in a decline in data quality, which in turn may affect the reliability of the study results. It is therefore essential to employ appropriate methodologies and analytical techniques when

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conducting fNIRS studies to ensure the robustness of the conclusions drawn [12].

In addition to data quality concerns, data processing also plays a crucial role. The selection of signal processing techniques has a substantial impact on the outcomes of fNIRS. Different signal processing techniques may yield disparate statistical results. For instance, a processing technique that neglects task-induced physiological noise in the fNIRS signal may produce implausible results. Consequently, it may be more realistic to employ a signal processing technique that corrects for physiological confounding effects (Fig. 1) [13].

Beyond data quality and processing, another important consideration is reliability. The test-retest reliability of fNIRS is also a crucial metric for evaluating its accuracy and reliability in diagnosing Parkinson's disease. Previous studies have demonstrated that fNIRS exhibits high test-retest reliability for cortical activity intensity and brain network metrics in the resting state [14]. This indicates that fNIRS can serve as a reliable tool for assessing the functional brain status of Parkinson's disease patients. While fNIRS shows promise in many aspects, it's important to acknowledge its limitations. Despite its advantages, fNIRS still has some limitations in comparison to other imaging techniques, such as functional magnetic resonance imaging (fMRI). For instance, the spatial resolution of fNIRS is typically inferior to that of fMRI, and its capacity to penetrate deep brain structures is constrained [11]. Moreover, interpreting fNIRS signals requires some understanding of how blood flow relates to brain activity, a concept known as neurovascular coupling [15].

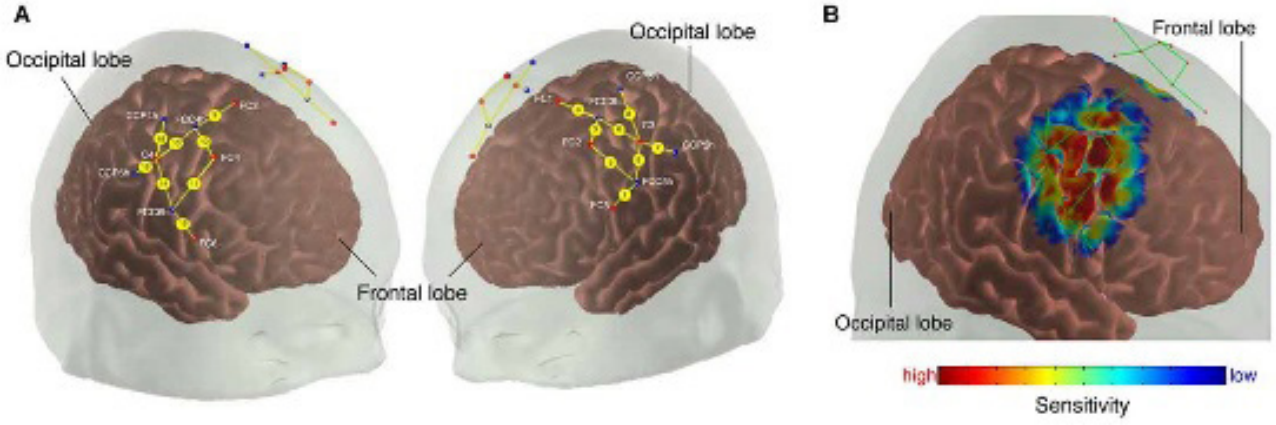

Fig. 1 (A) Probe array (B) Sensitivity profile [13]

2.2 Resting state and task state in the diagnosis of Parkinson's disease with fNIRS

Even when people are at rest, the brain is still active. This resting state is characterized by spontaneous low-frequency fluctuations (less than 0.1 Hz) in functional networks, reflecting the natural connectivity between different brain regions [16]. Resting brain functional connectivity is frequently designated as the "default mode network," which is notably active at rest and is observed in a multitude of background activities that are not associated with cognitive function [17][18]. In patients diagnosed with Parkinson's disease (PD), alterations in brain function at rest can manifest as early indications of the disease, such as functional deterioration or aberrant patterns of brain activity [19].

While resting state provides valuable information, it's also important to study the brain during active tasks. In the task state, the brain is required to perform specific cognitive or motor tasks, which can result in increased activity in certain regions. For example, during tasks such as the Verbal Fluency Test (VFT), significant changes in oxyhemoglobin and deoxyhemoglobin levels are observed in the brain, which can be captured by functional near-infrared spectroscopy (fNIRS) technology [20]. The functional connectivity of the brain during task states can provide information about how the brain responds to external stimuli, which is important for assessing cognitive and motor dysfunction in patients with Parkinson's disease (PD) (Fig. 2).

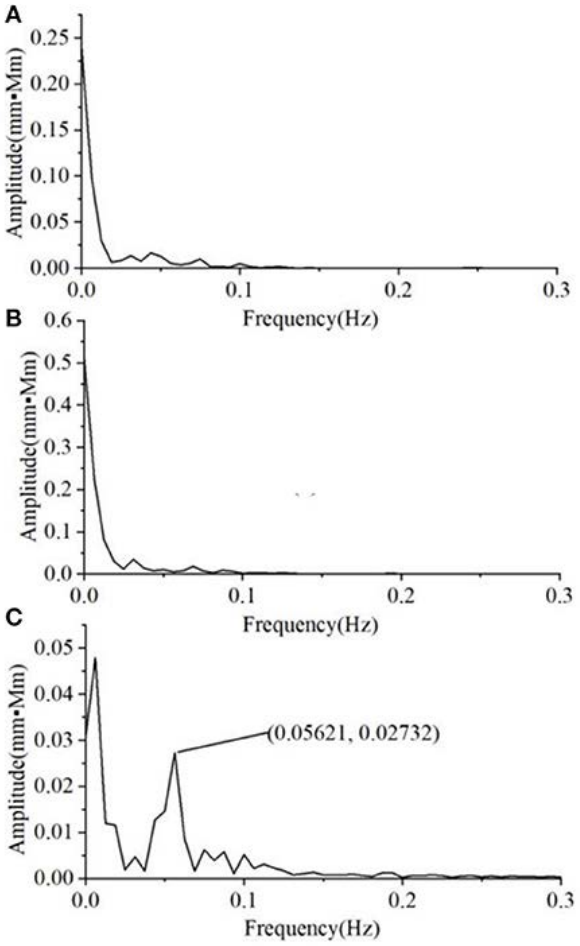

Fig. 2 The typical Oxy magnitude spectrum curve from a representative individual in each of three groups [20]

In the diagnosis and treatment of PD, the application of these two states can assist physicians in gaining a more comprehensive understanding of a patient's functional brain state. Resting state analysis enables the identification of PD-related functional changes, while task state analysis facilitates the assessment of the impact of PD on a patient's daily functioning. By comparing the differences in brain functional connectivity between PD patients and healthy controls in the resting and task states, the specific effects of PD on brain structure and function can be more accurately discerned [19][21]. This comprehensive approach combining both resting and task states provides a more nuanced understanding of PD's impact on brain function.

2.3 Specific applications of fNIRS used in combination with other biomechanical data in Parkinson's disease

In one study, brain activity was recorded using multiple techniques. Functional near-infrared spectroscopy (fNIRS) was used alongside electroencephalography (EEG) to capture changes in brain waves. Concurrently, an IMU-based motion capture system and WearUp gloves were employed to document both macro- and micro-scale body movements [22]. These data were utilized in a Support Vector Machine (SVM) classifier for classification purposes. The results demonstrated that the accuracy of distinguishing between PD patients and normal controls was markedly enhanced when fNIRS and EEG data were utilized in conjunction. This indicates that the integration of diverse biomechanical data types can facilitate more accurate PD diagnosis.

Another study proposed a new way to analyze fNIRS data to better understand how PD affects brain function over time. The method constructs dynamic functional connectivity through sliding window correlation analysis and applies k-means clustering to generate key brain connectivity states. A support vector machine was trained to distinguish PD patients from healthy controls by extracting dynamic state features, including state occurrence probability, state transition percentage, and state statistical features. The results demonstrated that PD patients exhibited a greater propensity to transition to brain connectivity states with higher levels of information transfer compared to healthy controls (Fig. 3) [23].

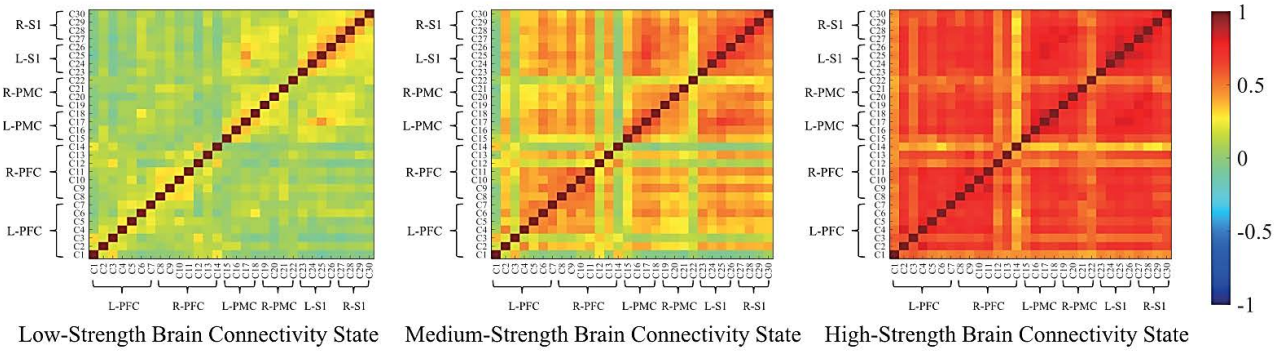

Fig. 3 Three key brain connectivity states, named low-strength, medium-strength, and high-strength brain connectivity states [23]

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Beyond static measurements, researchers have also explored how fNIRS can be used to study brain activity during movement. For instance, studies have employed an fNIRS-based experimental paradigm to capture brain activation in PD patients and healthy controls during dual-task walking. Three brain states were defined: dilated, contracted, and intermediate. Transition factors and corresponding transition features were extracted from temporal variations of oxyhemoglobin and deoxyhemoglobin responses. These features were used to train support vector machines to discriminate between PD patients and healthy controls. The experimental results demonstrate that this method is highly accurate in distinguishing between PD patients and healthy controls [19].

It is clear that combining fNIRS with other biomechanical data has multiple benefits. This approach not only improves the accuracy of PD diagnosis but also provides insights into how PD affects brain function and body movement patterns. These findings provide novel perspectives and tools for the early diagnosis and treatment of PD. As research in this area continues to advance, this paper can expect even more sophisticated and effective diagnostic and treatment strategies to emerge.

2.4 Signal processing for detection or treatment of Parkinson‘s disease using fNIRS

When using fNIRS to study Parkinson's disease, one significant challenge is dealing with motion artifacts. These are signal disturbances caused by head movement during fNIRS data acquisition of Parkinson's patients. To minimize this interference, several algorithms can be employed to identify and correct for motion-related signal changes. In one study, researchers compared eight different MAR algorithms and tested them while 23 young adult volunteers performed a grasping task. The results demonstrated that the single-channel MAR algorithm was the most effective before subsequent BPF and PCA processing [24].

Band-pass filtering is employed to eliminate irrelevant frequency components while retaining signals within a designated frequency range associated with brain activity. In the processing of fNIRS data, it is frequently necessary to filter out low-frequency respiratory disturbances (0.1-0.3 Hz), high-frequency cardiac disturbances (0.8-2.0 Hz), and other electronic noise. It has been demonstrated that the use of higher-order finite impulse response filters (e.g., 1000th order) can be an effective means of recovering the hemodynamic response from fNIRS data [5].

Beyond filtering, more advanced statistical techniques can also be applied to fNIRS data. One such method is Principal Component Analysis (PCA), a statistical approach for dimensionality reduction and feature extraction. In the analysis of fNIRS data, PCA can assist in identifying and interpreting major patterns of variability in the data. For instance, PCA enables the transformation of raw data into a new set of mutually orthogonal variables (principal components) that more accurately reflect changes in brain activity in Parkinson's patients. This approach enhances the quality of the signal and simplifies the subsequent process of data analysis [25].

3. Conclusion

The application of functional near-infrared spectroscopy (fNIRS) in the diagnosis of Parkinson's disease represents a promising and evolving field of research. This article examines the intricacies of fNIRS as a diagnostic tool, emphasising the pivotal role of data quality and processing in guaranteeing the technique's precision and dependability. The integration of fNIRS with other biomechanical measurements significantly enhances the diagnostic potential, offering a more precise understanding of the disease's impact on brain function. The application of advanced signal processing techniques, including motion artifact removal, band-pass filtering, and principal component analysis, is essential for refining fNIRS signals and enhancing the detection of Parkinson's disease and the development of effective treatment strategies. Furthermore, the chapter highlights the value of integrating resting state and task state assessments in the diagnosis of Parkinson's disease. By examining both states, clinicians and researchers can gain a more comprehensive understanding of the brain's functional status, which is crucial for a comprehensive and accurate diagnosis of Parkinson's disease. This comprehensive approach not only facilitates the immediate diagnostic process but also establishes the foundation for future advancements in the field.

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