

Evaluation of a Telemonitoring Interface for Neurodegenerative Disorders through Wearable Biosensors

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Abstract—Neurodegenerative disorders such as Parkinson’s disease, Alzheimer’s disease, multiple sclerosis (MS), and amyotrophic lateral sclerosis (ALS) often need long-term monitoring and personalized rehabilitation plans. This study is the first look at NÖRALSİS, a telemonitoring interface that uses wearable biosensors to help with remote assessment and rehabilitation. The system combines a web-based clinical platform with biosignal data acquisition using a wristworn device. The device captures multimodal signals such as electrodermal activity (EDA), photoplethysmography (PPG), skin temperature, and inertial movement. During this phase, the system’s architecture was built and tested with a healthy volunteer to see how well the sensors worked together, how good the data was, and how well the interface worked. Furthermore, the usability of biosensor-derived data was explored in the context of clinical monitoring scenarios such as physical exercise, rest, and posture control. Early results show that the system can reliably pick up high-resolution biosignals and connect them to user activities in a clinically useful way. The results show that the proposed platform could be used as a base for future patient trials that involve remote patient monitoring and personalized rehabilitation strategies.

Keywords—Telemonitoring, Neurodegenerative Disorders, Remote Rehabilitation, Wearable Biosensors, Postural Stability

I. INTRODUCTION

Neurodegenerative disorders pose considerable challenges owing to their progressive nature, diverse symptoms, and the necessity for enduring, individualized care strategies [1], [2]. Traditional clinical assessments are often episodic and lack ecological validity, making it difficult to capture dynamic physiological and functional changes in their daily lives [3]. The incorporation of wearable biosensors into telehealth platforms presents a viable solution for remote, continuous, and objective patient monitoring, allowing clinicians to meticulously track symptoms such as gait impairment, autonomic dysfunction, and cardiovascular anomalies with elevated temporal resolution [4], [5].

This study is the first review of proposed system, a prototype telemonitoring interface designed for patients with neurodegenerative diseases. The system combines a wearable

multimodal biosensor, with a web-based clinical dashboard to help with remote assessment and rehabilitation workflows. The current study focuses on validating the feasibility of the system using pilot data. In particular, we assess the quality of the signals to see how useful it is in simulated clinical situations like rest, exercise, and posture control status. This preliminary work sets the stage for future patient trials and the creation of smart decision-support mechanisms. Our purpose to create a scalable, patient-centered telehealth platform for the long-term management of neurodegenerative disorders by combining physiological monitoring with interactive clinical interfaces.

II. METHODOLOGY

A. System Architecture and Biosensor Configuration

The proposed telemonitoring system, NÖRALSİS, is designed to facilitate continuous and remote assessment of individuals affected by neurodegenerative disorders which contain two major components: (1) a wearable biosensor platform for physiological signal acquisition, and (2) a web-based clinical interface for data visualization, filtering, and clinician interaction. We used the Empatica EmbracePlus device for biosignal acquisition because it is clinically accurate, has CE certification, and has been approved by the FDA for research use, so allowing continuous, non-invasive monitoring without disrupting daily activity. The device can simultaneously record EDA, PPG, Skin temperature, 3-axis accelerometer and gyroscope. The web-based clinical dashboard shows clinicians a timeline of physiological data streams and how well participant are wearing their devices. You can get data in two ways: as minute-resolution summaries or as high-resolution raw signals. Using a Cyberduck interface, raw data is safely pulled from AWS S3 buckets and processed locally with custom Python pipelines for more in-depth analysis.

B. Data Collection Protocol

We evaluated the proposed telemonitoring system’s functionality with a healthy adult volunteer using a structured pre-

liminary data collection protocol. This protocol was construct to mimic common clinical situations in neurorehabilitation, such as physical exertion, passive rest, and postural challenge. We chose these conditions to test how good, reliable, and easy it is to understand biosignals in different physiological states. Before collecting data, the participant was asked to wear the device on the non-dominant wrist. The session conducted in a controlled indoor environment to reduce outside noise, with the temperature and lighting kept the same throughout. We paired the wearable device with the Empatica mobile app and verified for correct placement and signal acquisition. The protocol consisted of the following sequential phases:

- **Baseline Resting State** (5 minutes): The participant sat still and relaxed without talking or moving. During this time, baseline physiological signals were recorded. These provided reference values for autonomic and cardiovascular regulation when the body wasn't being stimulated.
- **Therapeutic Exercise Simulation** (10 minutes): To mimic rehabilitation exercises, we asked participants perform set of functional motor tasks as a standard physiotherapy routines. Movements included seated arm raises that focused on upper body activity, sit-to-stand transitions for activating the lower body, march-in-place much like walking, and lunge exercises which put their postural control to the test. With these tasks we aimed to elicit changes in EDA phasic responses, acceleration patterns, and BVP-derived heart rate changes while under physical load.
- **Post-Exercise Recovery** (5 minutes): After the active phase, the participant sat down to rest again. During this phase, data was collected that showed how the body was recovering, especially how heart rate variability (HRV) rebounded, body temperature returned to normal, and skin conductance level (SCL) decreased, which showed that parasympathetic tone had returned.
- **Postural Challenge Test** (3 minutes): The participant is asked to perform static lunge holds and weight-shifting movements while standing to assess their balance which is key for looking at both side-to-side (mediolateral) and front-to-back (anteroposterior) postural sway that cab be evaluate using accelerometer and gyroscope signals.

During the session, we continuously streamed biosignal data and upon completion then each phase was time-stamped and annotated for segment specific analysis.

C. Signal Preprocessing and Quality Assessment

A multi-stage signal preprocessing and quality assessment pipeline was set up to ensure that the biosignals collected by the wearable device were accurate. In this step, we aimed to reduce motion artifacts and physiological outliers especially given the ambulatory and multimodal nature of the data.

1) *Formatting and Synchronizing Signals*: Interpolation was used on signals when necessary to make sure that the sampling rates were the same across all channels. This made it possible to do multimodal fusion and phase-based analysis during different protocol segments, like rest and exercise.

2) *Quality Assessment of EDA Signal*: EDA signal were validated at using a rule-based artifact detection method primarily based on Kleckner et al. [6]. This framework gives a clear and adaptable way to score quality. We applied four main rules during the evaluation. First, we performed a physiological range check, marking any values outside $0.05\text{-}60\ \mu\text{S}$ as invalid. Second, signal jumps sudden changes greater than $10\ \mu\text{S}$ between adjacent samples were flagged as potential artifacts. Third, we identified flatlines, which are prolonged constant segments suggesting sensor disconnection or dry electrodes. Lastly, movement-related noise was detected by cross-referencing high-frequency EDA components with ACC data to spot any signal degradation caused by motion. Any segments that violated one or more of these criteria were then excluded from further SCR/SCL calculations.

3) *BVP and HRV Signal Validation*: BVP signal underwent low-pass filtering with a cutoff frequency of 5 Hz to mitigate high-frequency noise. We used a threshold-based method to find peaks and get inter-beat intervals (IBIs). From these, we calculated time-domain HRV features like RMSSD and SDNN. We applied physiologically plausible limits to identify and excluded artifactual IBIs like those resulting from missed or extra heartbeats.

4) *Temperature and Accelerometer Signal Filtering*: A moving average filter with a 10-second window was used to smooth out skin temperature signals and get rid of temporary sensor noise. We applied a 4th-order butterworth low-pass filter with a cutoff frequency of 2.5 Hz to effectively isolate postural and movement changes from noise in the accelerometer data. Subsequently, activity levels were quantified using derived metrics such as signal magnitude area (SMA) and derivative of acceleration.

5) *Segment Labeling and Annotation*: We labeled each time window in the data stream based on the activity phase, such as rest, exercise, or postural challenge. Signal quality scores were kept as metadata so that only valid segments could be analyzed. We made visualization plots to look at the shape of the signals and check the outputs of the preprocessing by hand, for example, EDA time series with quality flags and BVP with detected peaks (Figure 1).

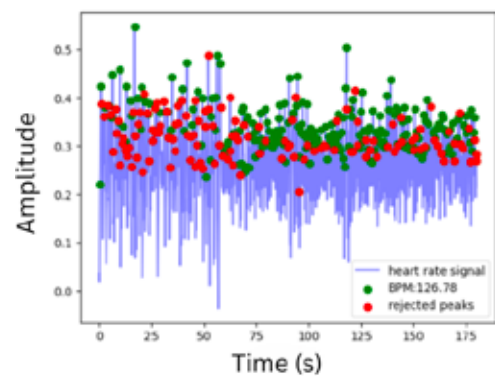


Figure 1: Rejected and accepted peaks for the BVP Signal during March-in-place

This strict method of preprocessing and quality control made sure that the analysis that followed was based on high-fidelity biosignal segments, which made it possible to accurately interpret the results in clinical monitoring and rehabilitation situations.

D. Feature Extraction and Scenario-Based Interpretation

After preprocessing and checking the quality of the signals, we took out domain-specific features from each biosignal to measure how the body responds to different clinical situations like autonomic nervous system, cardiovascular system, thermoregulation, and motor activity are working, since these are important in neurodegenerative diseases. Interpretations were then made based on structured use-case simulations, including exercise, rest, and postural control challenges.

1) *Features of Electrodermal Activity (EDA)*: We used continuous decomposition analysis to break down both the tonic and phasic parts of the cleaned EDA signal. The SCL was the tonic background level and was used to look at overall trends in arousal and stress. We measured the Skin Conductance Response (SCR) component by looking at the number of SCR peaks per minute, the amplitude of SCR responses, the rise time, and the half-recovery time to understand how the sympathetic nervous system works during exercise like frequent and large SCRs can be consider increased arousal, while tapering SCL is sign of recovery (Figure 4).

2) *Cardiovascular Features from BVP and HRV*: From the BVP signal, peaks were detected to derive IBIs. Subsequently, time-domain HRV metrics were computed to characterize the dynamics of the autonomic nervous system's influence on cardiac activity [7]. Among these metrics were values like Mean Heart Rate (HR), the Standard Deviation of NN intervals (SDNN), and the Root Mean Square of Successive Differences (RMSSD). For example, a drop in overall HRV during physical exertion typically points to increased sympathetic nervous system activity, while a higher RMSSD value during resting phases indicates that the parasympathetic nervous system is in recovery [8]. These measures made it possible to track on stress, fatigue, and autonomic balance in real time.

3) *Skin Temperature as a Means of Thermoregulation*: Skin Temperature measurements were recorded continuously at a sampling frequency of 4 Hz during different activity phases, such as sitting down to rest, doing guided physical exercises, and resting without doing anything. We aimed to capture variations in peripheral skin temperature as indicators of sympathetic nervous system engagement and thermoregulatory response. We normalized data into segments based on activity windows and for each segment, we calculated statistical descriptors like mean, slope, and range to describe how temperature changes with activity and recovery. These features are intended to support modeling autonomic responses, and they can also be used as covariates when making personalized rehabilitation monitoring algorithms.

4) *Movement and Postural Features from Accelerometer*: The accelerometer sensor was configured to record movement in three orthogonal axes (X, Y, and Z), which stand for

mediolateral, anteroposterior, and vertical directions, respectively which sampled data at 32 Hz. We extracted several metrics related to activity such as Signal Magnitude Area (SMA), step count and cadence, and crucially, postural sway trajectories in both mediolateral and anteroposterior directions. We determined these sway trajectories by projecting the acceleration vectors onto those specific planes, which allowed us to visualize them in plots similar to stabilograms. For tasks demanding static balance, such as single leg stands or lunges, we also employed moving average techniques to pinpoint the center of acceleration, and then used trajectory dispersion to quantify the sway magnitude.

5) *Interpretation Based on Scenarios*: We mapped all of the extracted features to three clinical scenarios that were simulated in the trial:

- **Monitoring Physical Activity**: High heart rate, SCR bursts, increased SMA, and temperature rise were signs of engagement and sympathetic response.
- **Resting-State Assessment**: A lower heart rate, a higher HRV, and a steady SCL showed parasympathetic rebound and autonomic restoration.
- **Postural Control Challenge**: Lateral and anterior sway vectors were visualized using accelerometer axes, showing stability trends and directional fall tendencies.

These scenario-based interpretations demonstrate the feasibility of linking raw biosensor data to clinically meaningful insights in real-time. Such interpretations can be directly integrated into decision support systems for tele-rehabilitation.

III. RESULTS

A. Signal Quality Validation

All sensor streams were successfully recorded without major interruptions. The rule based evaluation of EDA signals showed that 92% of the segments were in the range between 0.05–60 μ S. The remaining portions were flagged because of sudden discontinuities or flatlines. PPG signal showed strong peak detection correctly identifying 96 % of beats, which made it possible to reliably calculation of HRV indices. By cross-referencing accelerometer data, we were able to consistently find motion-related artifacts and leave them out of further analysis.

Table I: TIME-DOMAIN HRV METRICS

Segment	Mean-HR	RMSSD (ms)	SDNN (%)	pNN20
Rest	70.484	67.794	99.559	38.7091
Upper Body	94.743	53.273	96.002	29.090
Lower Body	125.284	61.304	81.262	25.252
March-in place	142.308	34.082	55.448	16.279
Lunge	158.611	22.652	25.054	2.923
Rest	95.813	43.959	92.147	9.726

B. Physiological Response Validation

Physiological responses corresponded effectively with anticipated patterns across various activity scenarios. During exercise heart rate increased by 125 % relative to baseline from 70.5 bpm to 158.6 bpm and HRV (RMSSD) decreased

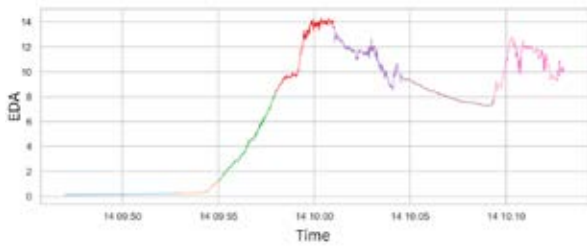


Figure 2: Electrodermal Activity across different segments

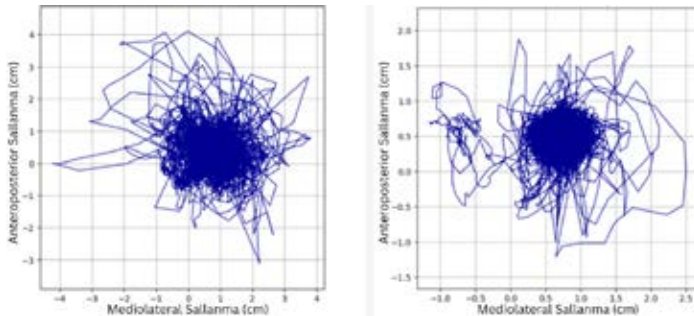


Figure 3: Postural Sway Comparison under (i) Unstable and (ii) Stable Conditions

by 67 % from 67.8 ms to 22.7 ms (Table Table I), consistent with sympathetic activation (Figure 2).

The HRV metrics indicate a clear physiological response to increasing exercise intensity. Mean-HR and sympathetic dominance reflected by lower RMSSD and pNN20 progressively increase during physical tasks, while overall variability SDNN drops. These trends show that the system works well for capturing autonomic modulation during exercise and recovery. At the same time EDA displayed frequent SCR peaks, while tonic SCL gradually rose. On the other hand, during rest periods, heart rate stabilized, SCR activity decreased, and SCL returned to its baseline level. Postural tasks exhibited quantifiable sway displacements (Figure 3), with mediolateral deviations surpassing anteroposterior ones, indicative of the biomechanical requirements of the lunge task.

C. Multimodal Consistency Validation

Cross-modal analysis exhibited consistent trends between biosignal. SCR peaks occurred simultaneously with increases in HR during exercise sessions ($r = 0.82$). Skin temperature showed a delayed but monotonic increase that followed the similar pattern as SCL ($r = 0.76$). Movement markers derived from the accelerometer were aligned with changes in cardiovascular and EDA responses. This showed that the system could put physiological signals into the context of behavioral states. Parasympathetic rebound during recovery was incomplete, with RMSSD recovering only 67% of baseline values despite HR normalization.

IV. CONCLUSION

This study presented the NÖRALSİS telemonitoring platform as an initial measure for the remote management of

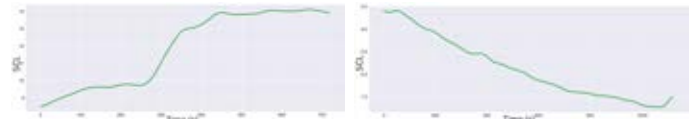


Figure 4: (i) March-in-place workout SCL in comparison to (ii) second resting segment

neurodegenerative disorders. The validation results showed that the data was very accurate. More than 92 % of the EDA segments and more than 96 % of the PPG-derived beats meeting quality criteria. Also, multimodal consistency analysis showed a link between SCR peaks and changes in heart rate ($r = 0.82$). The findings underline the feasibility of linking biosignal features to clinically meaningful state like sympathetic activation during exercise and stability recovery in rest. The study was conducted with a single healthy participant, limiting generalizability to patients with neurodegenerative disorders. Certain segments, such as static balance exercises, showed variable HRV responses, suggesting that further optimization of segment labeling and signal processing may be needed. Additionally, environmental factors and sensor placement could influence data quality, and the current analysis did not include long-term monitoring. Future studies should validate the platform with larger and more diverse patient populations. Despite these limitations the platform was successful in the tracking of autonomic and motor functions while establishing foundations for personalized rehabilitation through digital biomarkers.

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