A Study of Tremor Classification in Parkinson's Disease using Unsupervised Learning Methods and Wearable Sensor Signal Processing

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INTRODUCTION

Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized primarily by motor-related symptoms as tremor, slowness of movement, rigidity and difficulty with balance [1].

Although symptoms may vary from person to person, resting tremor is usually the most common symptom [2]. At the onset of the disease, it may be mild and unrecognized, and may only be a barely perceptible tremor in a hand, or sometimes in a foot or jaw. It often starts on one side of the body and then affects both sides, but usually one side remains the more affected than the other.

A diagnosis of PD is made based on neurological and physical examinations. The Movement Disorder Society Unified Parkinson's Disease Rating Scale (MDS-UPDRS) [3] is the most common clinical scale used to track the longitudinal progression of PD. The assessment is based on disease severity, as determined through interview and clinical observation. Therefore, the evaluation may be subjective and affected by variability, reflecting the need for more objective measures for tremor classification.

Machine learning algorithms have recently been used to process data collected by wearable sensors [4].

Aims: Explore the use of an unsupervised learning model (k-means) to solve two classification problems: CP1: distinguish patients from controls (i.e. tremor vs. non-tremor); CP2: classify different tremor severities, where k=n. We also consider a third problem, CP3, which aims to distinguish between severe and mild tremor (i.e. k = 2), with the aim of simplifying CP2.

METHODS

We used a publicly available dataset accessible via the website https://doi.org/10.21227/g2g8-1503 [5]. This dataset includes activity, gait, and tremor measures from 17 individuals diagnosed with PD and 17 healthy control (HC) subjects who were matched for age. These measures were collected using five adhesive sensors (one on each limb and one on the trunk) which captured triaxial accelerometer data during a clinic visit. Annotation files were also collected during this visit, when subjects underwent an evaluation using the MDS-UPDRS. We only considered data from sensors placed on the upper limbs of people with PD, and we excluded four subjects due to missing clinical data. Thus, our population included 13 PD patients (mean age ± SD: 66.1 ± 11.8 years; 38.5% female) and 11 HCs (66.0 ± 8.4 years; 90.1% female).

Before to apply k-means we performed a data segmentation process with the aim of extracting time intervals in which subjects were seated in a resting state. We used the start and end timestamps of the resting periods performed during the clinical assessment according to file tasks annotations. Then, the extracted segments were concatenated into a single string, i.e. a recording instance. We analyzed the tremor-predominant arm recordings for each PD patient, except for one patient for whom we analyzed both arms, for a total of 25 recording instances.

We pre-processed the raw accelerometer data performing the mean-centering and computing modulus. This transformation was necessary because of the effects of sensor orientation and individual bias. We chose the Euclidean distance as the distance metric because of its effectiveness in measuring the similarity of the movement intensities represented by the modulus values [6].

To ensure a balanced distribution of tremor events across subjects and enhance the sensitivity of the clustering algorithm, we only considered signal periods within the 95th percentile

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of movement intensity. We then identified the 'dominant cluster' as the cluster label that occurred most frequently in the top 5% of modulus instances.

In order to evaluate the accuracy of the K-means algorithm, we compared its assignments with clinician diagnoses. Specifically, for CP2, we compared cluster assignments with tremor labels assigned by the neurologist according to item 3.17 of the MDS-UPDRS, which evaluates resting tremor amplitude using a scale of 0–4. HCs had an at-rest tremor score of 0. Finally, we used a best matching approach to align the cluster labels with the clinical labels, selecting the mapping that resulted in the highest accuracy percentage among all possible permutations.

RESULTS

CP1: the algorithm achieved an accuracy of 76.0%. Specifically, most PD patients were correctly assigned to the tremor cluster, while the majority of HCs were assigned to the non-tremor cluster. CP2: The algorithm achieved an accuracy of 57.1%, with significant overlap in cluster assignments. CP3: The algorithm achieved an accuracy of 71.4%. Figure 1 shows the k-means performance in all CPs.

CONCLUSIONS

The results emphasize that raw motion data can provide valuable information independently of predefined clinical labels, achieving a high level of accuracy in distinguishing tremor states from non-tremor states. Although the results of tremor severity classification, especially in multiclass scenarios, demonstrate the complexity of subtle tremor differentiation, highlighting the importance of improving feature extraction to achieve greater accuracy, the usefulness of unsupervised learning to enable scalable and objective tremor analysis is clear. Integrating such models into wearable systems could improve continuous monitoring, enhance rehabilitation strategies, and support standardized clinical assessments. Future work should focus on developing advanced algorithms, enriched feature sets and larger datasets to enhance the robustness and generalizability of these models.

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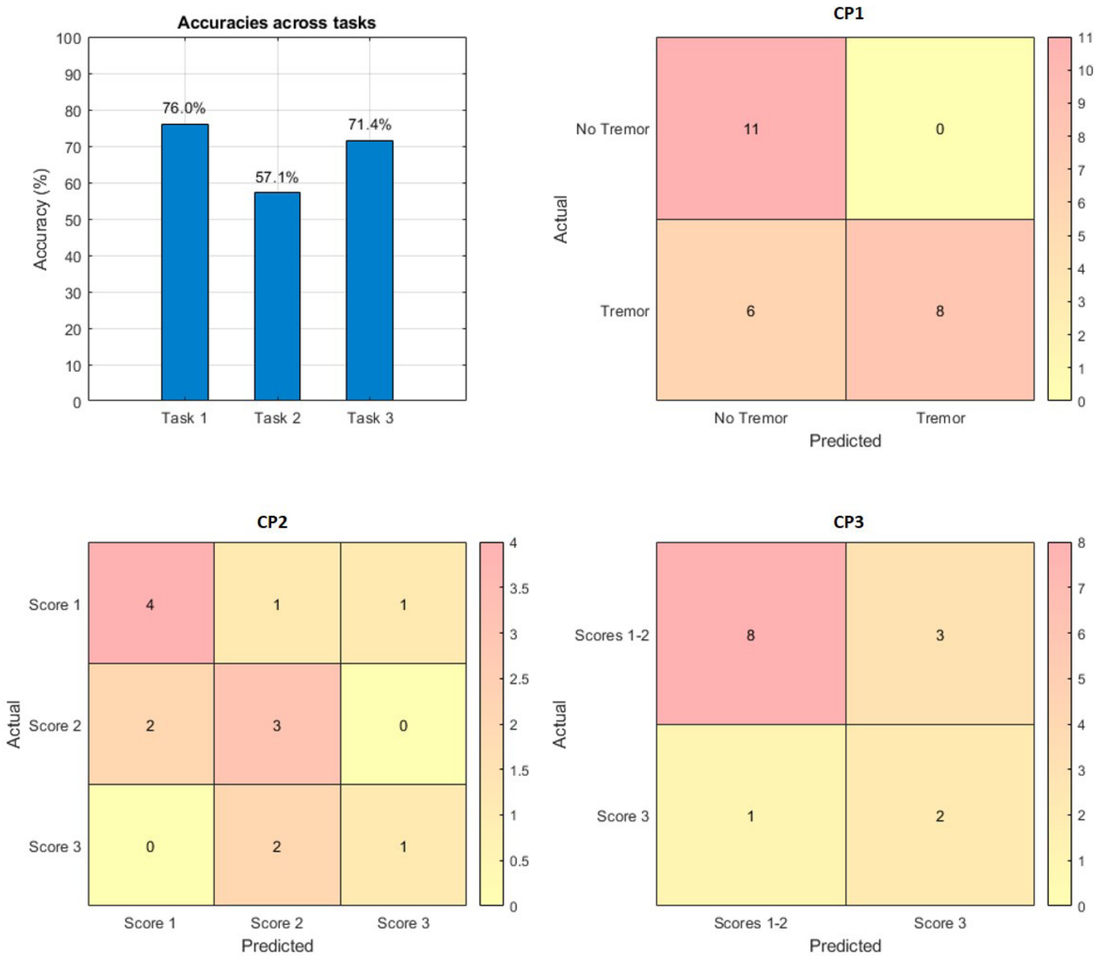

Figure 1. Classification tasks performances. The top left panel displays a bar chart summarizing the accuracy of each classification problem. The remaining panels provide confusion matrices for each CP, in clockwise direction: Tremor vs. Non-Tremor, Multiclass Tremor Severity, and Severe vs. Milder Tremor

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