The Transferable Methodologies of Detection Sleep Disorders Thanks to the Actigraphy Device for Parkinson's Disease Detection

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Abstract

Due to population aging, society is struggling with an increasing number of patients with neurodegenerative diseases. One of them is Parkinson's disease. Early detection of Parkinson's disease is very important since there is no cure and the treatment is more effective when administered early. Wearable devices can be of great help - they are cheap and reachable, they can last for many days without charging, can provide long time monitoring, and are minimally invasive to human life. In the paper, we briefly describe the sensors and actigraphs suitable for the analysis of sleep disturbance in Parkinson's patients and nocturnal symptoms of Parkinson's disease. Moreover, we pointed out how to collect the data and what could have an influence on the final performance of the automatic models. Additionally, as the main aim of this paper, we have analyzed and described the machine learning algorithms used in the area of analysis accelerometer signal for sleep / awake stages recognition or diseases which manifested in changes in sleep patterns. We thought that these algorithms, because of the nature of Parkinson's patients' sleep patterns, will be simultaneously appropriate for the detection of Parkinson's disease.

Keywords

machine learning, Parkinson disease, actigraphy, wearable device, IoT healthcare device, eHealth, Health 4.0

1. Introduction

Sleep plays a very important role in the health of people. If we could objectively measure its quality and quantity, it would be very beneficial for prevention and also early disease markers detection of future possible risks on the health. One of the diseases, which is connected with sleeping problems, is also Parkinson's disease. What is characteristic of persons suffering from Parkinson's disease are changes in their sleep stages. The typically visible markers with the sleeping problems are Rapid Eye Movement Behavioral Disorder (RBD), insomnia, Restless Leg Syndrome (RLS), Excessive Daytime Sleepiness (EDS), and breathing difficulties and are observable in the early stage of the disease [1, 2, 3, 4].

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To clarify, early detection is regarded as an approach to recognise the disease in the early stage of progression [5].

For the detection of sleep disorders, many approaches have been used so far: for example, bed sensors, wearable devices (including smartwatches), ultrasound, radiofrequency (RF), WiFi sensors, videosomnography, sleep diaries, electroencephalography (EEG) [6]. However, the gold standard in medical practice is still considered polysomnography (PSG), and it is considered the most robust medical examination nowadays [6].

PSG can evaluate sleep disorders using various modalities. It includes registration of oximetry records, respiration, electromyography (EMG), EEG, electrocardiography (ECG) and electrooculography (EOG) [7]. There exist also other tests like Continuous Positive Air Pressure, Videosomnography (VSG), and accelerometry. Unfortunately, they are also tedious, more expensive, and uncomfortable for the patients since often require hospital conditions to perform them [6]. This is the reason, why this approach struggles to detect possible issues in their early stages.

The main contribution of this paper is an overview of emerging methodologies regarding the detection of sleep disorders likewise the identification and comparison of the recent work. It was additionally presented the summary of differences of Parkinson's disease patients to healthy controls from the point of view of wearable sensors. The paper focuses on the application of convincing approaches, which are more suitable for home usage, like smart wearable electronics (e.g. actigraphy device) for recognition of sleep disorders of Parkinson's patients. The devices are more comfortable to patients and can be used for early markers disease detection.

2. Sensors and actigraph devices for registering movement

Actigraphy is a term for a non-invasive method for monitoring human rest/activity cycles and movements. It is being used for monitoring resting time, sleeping time, activity time (e.g. for fitness evaluation), or progression of diseases. The wearable actigraph devices are commonly equipped with sensors like accelerometers, gyroscopes, and magnetometers for the registration of movement, rotation, and body position. Additional functionality could be provided by surplus measurements such as heart rate, ambient light, skin temperature, skin conductance, and sound [8], [9].

Several types of actigraphs are available on the market. The most commonly chosen are 9-axis IMU (made by mbientlab), wGT3X-BT, ActiGraph GT9X Link (ActiGraph), GENEActiv (Activinsights), Actiwatch Spectrum Pro (Philips Respironics), Charge 3, Versa (Fitbit), Ticwatch E (Mobvoi), Vapor (Misfit), Vivoactive3 (Garmin), and Fit2 Pro (Samsung) [10]. The placement of an actigraph device is important for the analysis outcome. It could be situated on wrists, ankles, thighs, or hips. The most information-rich placement of the wearable device seems to be the wrist, especially this is true in the case of Parkinson's patients [11].

2.1. Sleep disorders detection in Parkinson's Disease (PD)

Depending on the disease, various correlations of results obtained by actigraphy versus PSG would be observed. Very promising results could be achieved for sleeping apnea or brain injury. However, specificity may differ significantly from sensitivity in the case of insomnia [8], [12]. For this reason, analyzing and deep understanding of the signal character of Parkinson's patients likewise consequently choosing an appropriate methodology for this problem will be crucial. One of the most important differences in the sleep pattern between PD patients and healthy control are: lower sleep efficiency (SE), longer wake after sleep onset (WASO), higher fragmentation index (FI), shorter total sleep time, and sleep onset latency (SOL) [13]. Furthermore, the patients with Parkinson's express nocturnal hypokinesia [14]. The symptom shows significantly fewer episodes of turns in bed than their spouses. The acceleration and velocity of the body are registered as slower likewise fewer degrees. Additionally, they are spending more time in the so-called supine position and they exhibit akinesia, which is especially visible in the second part of the night. The reason is the decreased level of dopamine secretion. The other symptoms that can be recognized in PD are restless leg syndrome, periodic limb movement, and chronic insomnia [15]. Taking into consideration the aforementioned symptoms, we are going to briefly present and compare the possible algorithms and methodology suitable for this problem.

3. Data processing, storage, algorithms and methodology

3.1. Data processing and data storage

The concept of how the data are being transferred from the actigraph devices is similar to all the devices and uses the approach of the Internet of Medical Things (IoMT) [16]. IoMT consists of data acquisitions, communication gateway, and server/cloud steps. The gateway is a transfer point between the device and cloud/server with the field connectors. It could be a physical device (for instance a smartphone [17] or some software). The most common communication protocol for connecting smartwatches with the gateway is Bluetooth, however, it is not limited to only this solution. The Wi-Fi and ZigBee communications are also using for data transferring [18], [19], [20], [21]. Cloud computing is dedicated to data storage, complex computations, limiting the usage of the wearable device, and automatic support system for decision making. The development in the quality of sensors, IoT devices, and cloud services allowed the development of telemedicine, which is desirable especially for monitoring elder people [18].

Several symptoms of Parkinson's patients could be monitored remotely with the usage of telemedicine by physicians and measured by sensors such as bradykinesia, tremor, sleep, freezing of gait, and also some other disease indicators [22]. One of the instances of the application dedicated to PD is the mHealth framework which is recognizing this disease based on gait analysis [23]. The data are acquired from the accelerometer, which is included in most of today's smartphones, and are sent to the cloud. The authors claim the system achieved 81 % accuracy.

The data could be sent in two forms as the raw signal or the so-called recording modes. There are three types of recording modes as the pre-processing step, i. e.: zero-crossing mode (ZCM), the time above threshold (TAT), or the proportional-integral mode (PIM). By using a mode, it is possible to limit the size of the data transmitted, however, it can also reduce the final accuracy of the support decision system [8]. Other factors like sampling frequency, time window (so-called epoch), or placing the actigraph will also influence the final model. 20-25 Hz is regarded as a sufficient sampling frequency, and going beyond 25 Hz, the data will commonly bring not more information [24].

It is crucial to know that the manufacturer sets the length of the epoch by default. The most common chosen length is 30 s or 1 min, a reduction in the length of the time window will result in a decrease of the prediction [25], [24].

3.2. Algorithms and methodology

This subsection describes the methodologies and algorithms that have found application in the detection of other diseases and cases based on wearables sleep disturbance records. Additionally, it contains examples of solutions for the identification of Parkinson's disease based on different modalities. To compare those existing approaches, the summary of potential methodologies for detection Parkinson's disease detection based on sleep disorders are presented in Tab 1. The overview and comparison of used approaches, features extractions, architectures were provided. Moreover, the obtained results of methodologies with comments to the carried-out experiments are added. The events counting analysis (or so-called activity counting) is one of the most frequently used approaches for detecting awake/sleep stages. Unfortunately, in the case of Parkinson's disease, the analysis cannot depend only on relatively simple sleep statistics or sleep behaviour analysis. Activity counting cannot give enough information about the disease progress or presence [26].

Depending on the manual or automatic feature extraction we distinguish between two categories of machine learning algorithms used for the analysis: so-called Shallow Learning or so-called Deep Learning. The algorithms used in the first class are usually the k-nearest neighbor (k-NN), Support Vector Machine (SVM), XGBoost, Naive Bayesian classifier, or Random Forest (RF) [24]. End-to-end learning is typically some kind of deep convolutional neural network. Since in this field there is a typical lack of data, the shallow methods have still relatively competitive results.

Various features can be extracted, which are typically related to the time domain, statistics, or also morphology-based. Also, the Fourier Transform or Wavelet Transform [27], which analyses frequency characteristics of the signal, is being used. There are many feature extraction methods from raw signal or activity counts for sleep analysis. They often include the energy of the signal, maximum, minimum, variance, skewness, kurtosis, entropy[28], basic spectrum component, maximum frequencies, root mean square (RMS) value of signal components, the difference between maximum and minimum signal peak values, the median normalized frequency of the signal's spectrum, the mean normalized frequency of the signal's spectrum [29], 10th, 20th, 50th, 75th and 90th percentiles, mean, the sum of values, standard deviation, coefficient of variation, peak-to-peak amplitude, interquartile range, signal power, peak intensity, zero crossings, time above threshold [30], crest factor, band energy, and spectral flux [31].

We have analyzed the potential application of deep learning architectures for Parkinson's' sleep disorders. They have been applied so far for the detection of sleep-related diseases, sleep/awake status, or also daily activities. In most cases, the convolution neural network (CNN) or time-aware architectures like long-short term memory (LSTM), Gated Recurrent Units (GRU), or their combinations were applied for this aim [32], [33], [28]. Modern possible approaches for time-series analysis include also temporal CNN's [34] or ODEs [35]. Because of the similarity of the accelerometry signal to the fluctuated speech signal, the promising and interesting solution for this purpose is the usage of spectrogram and subsequently, CNN [28].

One medical dataset problem could often be their small amount of data, which could significantly influence the resulting accuracy. This is often a reason for not sufficient accuracies. One possible solution for this issue is the usage of any of the data augmentation methods. In [27], it was introduced 3D augmentation, i.e. timewise scaling, magnitude scaling, and random rotation. Also, the normalization of the data and dealing with an imbalanced dataset are regarded as essential steps in creating robust models. The authors used smartphone-collected data that came from DREAM Parkinson's Disease Digital Biomarker Challange [36]. The gait of patients was recorded, which will be characterized by changes in walking pace, irregular cyclic pattern, or tremor during the quiet standing period. They have outperformed the state-of-the-art results thanks to normalization, augmentation, and CNNs. They achieved a 0.87 area under the curve (AUC).

Another work [10] compared the data from high-end sleep laboratory device (Newcastle polysomnography) and data measured by a wearable device on the wrist. In particular, the accelerometer sensor was used for the experiment. The author considered the sleep/awake stages and succeeded in 80 % accuracy for original data and 84 % accuracy after using the Synthetic Minority Over-sampling Technique (SMOTE) method dedicated for imbalanced data. The XGBoost was used as a classifier in combination with cross-validation for statistical evaluation of the data.

In [30], the authors evaluated person-related factors such as age, biological factors, or lifestyle-related variations for creating the algorithm for detecting sleep/wake periods. The data were first normalised in the pre-processing step, and 18 statistical features were extracted. In total, 21 actigraphy measurements were used. As the classifier, plenty of classifiers have been evaluated, including XGBoost, Naive Bayes, Regularized logistic regression (RLR) with an L2 regulariser and Stochastic gradient descent (SGD), Random forests (RF), AdaBoost (AB). The best performance was achieved using XGBoost, which reached 86 % accuracy, 95 % specificity, and 45 % sensitivity.

Other researchers have been recognizing Attention-Deficit/ Hyperactivity (ADHD) thanks to the analysis of the subjects' motion with the usage of accelerometers and gyroscopes. The model was trained using SVM using earlier mentioned features where feature selection optimization was used (they selected 15). Half of the features belong to "high-resolution histograms", and it is considered a good early marker of the ADHD disease by some scientific works. They have obtained 95 % accuracy [37].

In another work, the researchers converted the triaxial accelerometer signals into spectrograms. They have tested their architecture on three datasets, including the Daphnet freezing of gait dataset of PD patients. The methodology is composed of two steps: the unsupervised pre-training step and the supervised discriminative step. With the usage of Deep Belief Networks, they succeeded in freezing gait recognition in 91.5 % accuracy [28]. This pre-training (i.e. with features extraction) allowed achieving a better quality of predictions.

Other scientists also used CNNs with spectrograms, but for ADHD recognition, and obtained 98.6 % accuracy for 300 seconds window length. Furthermore, they have used the aggregate signal as the magnitude of the three-axis and normalization of the data. They have also prefiltered the signals with lower activity not to interfere with them with the valuable signal for detecting ADHD. They found that the choice of the window length influences the obtained accuracy. The best results were achieved using medium size window length [38], however, for Parkinson's disease, it could differ.

The next application of neural networks for analyzing sleep was mentioned in [31]. The authors have used Deep-ACTINet, which contains 1-D CNN and LSTM for sleep/awake status detection. They compared this method with another machine learning algorithm such as RF, Naive Bayes, Linear Discriminant Analysis (LDA), feature-based CNN, and two older, relatively frequently used algorithms: Sadeh and Cole-Kripke. The proposed model has outperformed the rest of the algorithms and has achieved 89.65 % accuracy.

Very interesting time-aware and low-cost architecture were presented in [33] for predicting Alzheimer's disease with actigraphy data: Time-aware Toeplitz Inverse Covariance-based Clustering (TICC) and CNN (TATC). TICC is an unsupervised method dedicated to recognizing states such as sleeping or exercising, and CNN can learn temporal features from time series. Subsequently, it is using a time-aware solution to capture circadian rhythm. The novelty lies in time series classification methods since the previous methods were not able to distinguish between those signals which were recorded at a different time of the day. For example, at night and during the day. This time-aware mechanism can consider the crucial part of the day as much more meaningful than data taken at another time. Whereas architectures like LSTM or GMU could analyze the long-term temporal dependencies. The authors used a combination of these approaches have achieved 86.2 % AUC and, on the comparable level the sensitivity and specificity.

Other researchers used the bidirectional version of LSTM for sleep / awake recognition, where they achieved 96.5 % accuracy[9]. They used the signals of 3-axis acceleration and skin temperature and tested various signals, but those mentioned above were reported to be the best. They have highlighted that real-time LSTM gave results smaller by 0.2-1 %, so this solution will be adequate for real-time application.

The bradykinesia symptom was analyzed for the detection of Parkinson's disease with the usage of deep learning in [32]. The authors outperformed state-of-the-art methods by at least a higher 4.6 % accuracy. The results were also compared with algorithms like AdaBoost, k-NN, SVM, but they achieved worse accuracies than the previous works. The patients had to execute specific motor exercises and thanks to the 3-axial accelerometer, it was possible to detect the bradykinesia. They used CNN and reached 90.9 % accuracy.

Table 1

Potential methodologies for detecting Parkinson disease detection based on sleep disorders

Main Aim	Features/Architectures	Results	Disease/Case	Comments
Evaluation of temporal and spatial augmentation [27]	Deep convolutional neural network	0.87 AUC	The gait of PD patients	Data augmentation improved the prediction
Testing XGBoost and SMOTE for sleep/awake stages detection [10]	XGBoost	80 % accuracy, 84 % with SMOTE	Sleep/awake stages	Using SMOTE improved accuracy, XGBoost was a good choice of algorithm
Evaluation of the performance of personalised factors, Testing various algorithms [30]	Features: 10th, 20th, 50th, 75th, and 90th percentiles, mean, sum of values, standard deviation, coefficient of variation, peak-to-peak amplitude, inter quartile range, skewness, kurtosis, signal power, peak intensity, zero crossings, time above threshold, and maximum value Algorithms: XGBoost, Naive Bayes, Regularized Logistic Regression with L2 regularizer, SGD, AdaBoost	86 % accuracy, 95 % specificity, 45 % sensitivity	Sleep/awake stages	Personalised sleep/awake prediction is better, the best observable results for XGBoost
Detection of ADHD [37]	Features extracted from accelerometer and gyroscope records, SVM	95 % accuracy	ADHD in children	It is possible to recognise ADHD in children. Needed extension of the database
Usage of CNN and spectrograms for Detection of ADHD based on 1-day record [38]	CNN + spectograms	97.62% sensitivity, 99.52% specificity, AUC values over 99%	ADHD	Deep learning together with actimetry records allows detecting the ADHD
Converting triaxial accelerometer signals into spectrograms [28]	Unsupervised pre-training step, supervised discriminative step, Deep Belief Networks, hybrid approach of deep learning and Hidden Markov Models	91,5 % accuracy	Freezing of Parkinson's gait	Pre-training with feature extractions allows achieving better prediction
Detection of Alzheimer disease in the early stage with time-aware NN [33]	Time-aware Toeplitz Inverse Covariance-based Clustering (TICC) and CNN (TATC)	86.2 AUC	Alzheimer disease	The great potential of using TICC for predicting Alzheimer disease
Comparison of the proposed method with different solutions [31]	Deep-ACTINet (1-D CNN and LSTM)	89.65 % accuracy	Sleep/awake	Achieved detection of sleep/awake stages with the end-to-end deep learning model
Testing bidirectional version of LSTM for sleep/awake stages [9]	Bidirectional LSTM	96.5 % accuracy	Sleep/awake	The solution adequate for real-time application obtained good results
Comparing algorithms according to the detection of bradykinesia [32]	CNN	90,9 % accuracy	bradykinesia	CNN outperformed other algorithms about 4.6 %
Checking if it possible to automatically detect periodic limb movements and actigraphy analysis could give results as PSG [29]	Time-based, frequency-based and signal morphology-based features, Linear discriminant analysis	74,2 % accuracy	periodic limb movements	Actigraphy records with support system methodology could serve as a method for recognising periodic limb movements
Personalised detection of sleep/awake stages [30]	10th, 20th, 50th, 75th, and 90th percentiles, mean, sum of values, standard deviation, coefficient of variation, peak-to-peak amplitude, inter quartile range, skewness, kurtosis, signal power, peak intensity, zero crossings, time above threshold, and maximum value, with normalized actigraphy measurements, NB, RLR, SGD, RF, AB, XGBoost	Up to 91% accuracy	Sleep/awake	The differences in sleep patterns were confirmed between the groups, the highest results were registered for AB and XGBoost

4. Conclusion

The emerging wearable devices seem to be promising tools for early symptoms detection of (not only) Parkinson's disease and a new trend for modern medicine. Its early detection is essential since no cure exists, and early treatment administration leads to significantly more effective treatment. Sleep analysis of PD patients seems to be a key for early marker detection.

In the scope of this paper, we have covered the recent works in this area, have made a comparison of accuracies, approaches, and applications, and identified the most promising methods for the future.

Thanks to wearable technology and its development in recent years, the sleep monitoring of patients based on actigraphy devices could be easily deployed as a common practice of eHealth solutions. Based on the literature review, it was confirmed that sleep metrics are statistically different for PD patients versus healthy control. The changes in the sleep stages are much more visible during the second part of the night because of the decrease in dopamine level. Based on this assumption, we have analysed various approaches and architectures of deep learning, which could be successful with sensor-based asymmetry in automatic analysis of Parkinson's disease. There are a couple of factors that could significantly impact the final accuracy of the detection. For example, the choice of modalities for transferring the data, selecting the length of the time window, data normalisation, the size of the dataset and its quality, data augmentation, feature selection, or dealing with the imbalanced dataset. XGB seems to be the most successful among other classical machine learning algorithms, together with feature extraction and selection. The usage of spectrogram and CNN, likewise time-aware neural networks such as LSTM, GRU, 1-D CNN, or their combination will be a promising approach for detecting sleep disorders in Parkinson's disease. The TICC architecture is especially noteworthy because of the possibility of considering the time of acquisition of the signals and recognising the long-term dependencies in the signal. Additionally, also considering the versatility of signals from sensors could bring more information and better performance of the final model.

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