Poincaré plot analysis for sleep-wake classification of unseen patients using a single EEG channel

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***Abstract*— This study explores automated sleep-wake classification using Poincaré plots derived from a single EEG channel. In order to quantify the Poincaré plots and utilize them for the distinction of sleep and wake states of the healthy individuals and patients with sleep disorders, various descriptors are computed. The most commonly used standard descriptors are SD1 and SD2, which determine the width and length of Poincaré plot. Along with SD1 and SD2, the ratio of SD1 to SD2, area of the Poincaré plots, energy of the slopes, and offsets obtained by linear fits to Poincaré plots with distinct lags, standard deviation, and complex correlation measure are also computed. Random undersampling with boosting technique (RUSBoost) is adopted to deal with the class imbalance problem. The performance of the method is evaluated on three different publicly available datasets by using 50%-holdout and 10-fold crossvalidation techniques. We achieved crossvalidation accuracies of 98.2%, 96.0%, and 94.4% for Sleep-EDF, DREAMS-Subjects and DREAMS-Patients datasets, respectively, by utilizing only eight features, and a single EEG channel. Furthermore, for the patient population with various sleep disorders such as mixed apnea, periodic leg movement syndrome, sleep apnea-hypopnea syndrome, and dyssomnia, we obtained average sensitivity of 96.8%, precision of 95.6%, and F1-score of 96.2%, for the sleep state; and 88.3%, 91.3%, and 89.8%, respectively for the wake state. Our results are comparable to or better than the existing studies in the literature. Further, the classification accuracies for the patients with a model trained only on the healthy population are quite impressive. Thus, the model is effective and generalizes well for the patient population.**

***Index Terms*— EEG, Poincaré plot, sleep disorders, sleep, wake, hypnogram, RUSBoost, classification, generalization**

I. Introduction

Sleep is extremely important for our physical and mental well-being. Any compromise in the quality of sleep such as sleep deficiency or fragmented sleep results in various health problems. Sleep-related disorders such as apnea, periodic limb movements in sleep, narcolepsy, and insomnia are prevalent yet remain unidentified or misdiagnosed [1]. The diagnosis is achieved through manual scoring of overnight polysomnography (PSG) data, which are generally collected in clinical settings with multiple electrodes attached to the patient's body. This results in further sleep disturbances and hampers the natural sleep cycle. Hence, there is a need for automated sleep analysis using minimal number of channels and minimal computational requirements. Such a system can provide an objective, efficient and faster way of scoring. Sleep is broadly divided into two categories, namely NREM (non-REM) and REM (rapid eye movements). The NREM sleep is further sub-divided into different stages i.e. N1, N2 and N3 based on the specific signatures of sleep waveforms. The sleep epochs are staged on the basis of standard scoring criteria such as Rechtschaffen and Kales (R&K) [2] or American Academy of Sleep Medicine (AASM) [3]. The annotation of sleep data into different stages as per the scoring rules are conducted by sleep experts. However, this manual scoring is time-consuming, expensive and also suffers from subjectivity and inter-rater variability.

A number of studies are ongoing to develop an automated sleep stage classification using a single EEG channel. Different techniques involving spectral bandpowers, empirical mode decomposition, complexity, time-frequency, graph-theory, functional connectivity, and/or non-linear analyses have been employed for the classification of sleep stages with varying degree of success [4–11]. Zhu et. al. [4] utilized graph domain features, namely mean degree and degree distribution by mapping the sleep EEG signal into a visibility graph. These features were fed to a support vector machine (SVM) for the classification of sleep into different states. Ganesan et. al. [5] used spectral bandpower ratios and Lempel-Ziv complexity measure as features with a linear classifier for classifying single-channel EEG data into sleep and wake states. Another work by the same authors [6] obtained a high accuracy of around 98% in classifying sleep and wake states by using a combination of features from EEG and EOG channels and SVM with a gaussian kernel. Sharma et. al. [7] applied iterative filtering to decompose EEG into amplitude-modulated (AM) and frequency-modulated (FM) components. Various features from amplitude envelope and instantaneous frequency of modes obtained by iterative filtering fed to a random forest classifier provided a high accuracy of 98% for sleep-wake classification. Bajaj et. al. [8] employed multi-class SVM and time-frequency features obtained using smoothed pseudo Wigner-Ville distribution on sleep EEG data for 5-class and 6-class classification of sleep. A study by Hassan et. al. [9] used ensemble empirical mode decomposition and derived statistical moment based features for sleep-stage classification. Anusha et. al. [10] utilized functional connectivity between the midline EEG channels for the analysis of different conscious states in sleep and wakefulness. Gupta and Pachori [11] used Fourier-Bessel decomposition to resolve the EEG into intrinsic band functions and employed convolutional neural networks to perform sleep staging.

This work utilizes Poincaré plot from a single EEG channel to classify sleep and wake states. Poincaré plot is a phase-space based approach which has been widely used

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in heart rate variability analysis [12–14]. A Poincaré plot is created by plotting a signal $x(k)$ against its delayed or lagged version, $x(k+\tau)$. The shape and other features of the resulting scatter plot depend on the nature of the signal, and provide valuable information about the long-term and short-term variability present in most of the physiological signals. PP analysis is computationally simple and thus facilitates real-time assessment. However, it has been less explored for the analysis of EEG signals, especially sleep EEG data. This study applies various descriptors to quantify Poincaré plots for classifying the sleep from wake state of healthy subjects and patients.

Accurate detection of sleep and wake states is helpful in the timely diagnosis and prognosis of comatose patients [15] and various sleep disorders like insomnia or apnea. The highlights of this work are: (1) exploring different descriptors to characterize Poincaré plots, (2) analysing their utility in sleep-wake classification, and (3) investigating the performance on a patient population with various sleep disorders.

The rest of the paper is organized as follows: Section II presents a detailed description of the dataset and the methodology considered in this work. The results reflecting the model performance are discussed in Section III and the conclusion is presented in Section IV.

II. Materials and Methodology

A. Experimental Dataset

In this work, we have used three different datasets, namely DREAMS-Subjects [16], DREAMS-Patients [16] and Sleep-EDF [17] datasets. All the three datasets are publicly available and comprise overnight polysomnography recordings. The DREAMS-Subjects and DREAMS-Patients datasets include three EEG channels (CZ-A1 or C3-A1, FP1-A1 and O1-A1), one EMG channel, and two EOG channels of 20 healthy subjects (20-65 years old) and 27 patients (19-74 years old) with various sleep disorders (mixed apnea, periodic limb movements of sleep (PLMS), sleep apnea-hypopnea syndrome (SAHS) or dyssomnia. Both datasets provide expert scores with AASM as well as R&K scoring criteria. In these two datasets, R&K scoring is performed with 20 sec epochs, while AASM scoring is done on the basis of 30 sec epoch length. The Sleep-EDF dataset comprises two EEG channels (FPz-Cz and Pz-Oz) and one EOG channel data from 8 subjects (21-35 years old); out of which four are healthy and four have mild sleeping difficulty. The experts have scored this dataset with 30 sec epochs based on R&K scoring criteria.

We have utilized a single EEG channel, namely Cz-A1 for DREAMS-Subjects and DREAMS-Patients dataset, and Pz-Oz for Sleep-EDF database. These EEG channels are chosen since they provided maximum accuracies for different sleep stage classification problems in our previous studies [5, 6, 18, 19] employing other approaches. The details of the epoch distributions of sleep and wake states for different datasets are listed in Table I. Since this study focuses only on sleep-wake state identification, we merged all the sleep stages, namely NREM (S1, S2, S3, and S4) and REM together as sleep state. We considered R&K scoring criteria as ground truth for all the datasets.

TABLE I
Distribution of sleep and wake stage epochs in different datasets employed for this study

Dataset	# Subjects	Wake	Sleep	Total Epochs
DREAMS-Subjects	20	5546	23187	28733
Sleep-EDF	8	8055	7133	15188
DREAMS-Patients	27	11573	30083	41656

B. Methodology

The workflow of this study is as follows: The raw EEG signal is filtered using an 8th order Butterworth bandpass filter with a passband of 0.5-49.5 Hz. Then it is segmented into 20 or 30 sec epochs, based on the ground truth format. Next, Poincaré plots are generated using pairs of consecutive points $(x(k), x(k+1))$. Examples of the resulting scatter plots are shown in figures 1 and 2. These figures present the Poincaré plots (PP) for sleep and wake states of a subject and a patient, respectively. It can be seen that the dispersions along the diagonal line (line of identity) as well as along the perpendicular direction to the diagonal are quite different for the two states in both cases. Hence, the idea is to derive different features describing the length, width and area of these plots to distinguish between the sleep and wake states. Eight features, namely SD1 (width), SD2 (length), SD1/SD2, S (area), CCM (complex correlation measure), standard deviation of each epoch, energy of the slopes and offsets obtained after fitting a linear regression model on the multiple lagged PP (lag τ varied from 1 to 100) are extracted from these plots. These features are then smoothed using a moving average filter of window size 35 samples (empirically chosen) and fed to a classifier. The outcome of the classifier is a binary hypnogram which represents the two states i.e., sleep and wake, across the entire duration of the sleep.

1) Feature Extraction: We derived eight different features by quantifying the Poincaré plots of the sleep EEG signal. The two standard descriptors which are widely used to characterize PP are SD1 and SD2 [13]. SD1 is the standard deviation of the distribution of points around the line perpendicular to the identity (also referred to as its width) and SD2 is the standard deviation around the identity line (referred to as the length of PP). Apart from these standard descriptors, a few studies have also utilized SD1/SD2 to determine the depth of anaesthesia [20, 21]. Therefore, we have used SD1, SD2, SD1/SD2 and the area of the elliptical structure formed by the scatter plots (with semi-major axis as SD2 and semi-minor axis as SD1) as descriptors of the PP. We have also looked into the variation of the data in sleep and wake epochs, and found that the standard deviation of each of these epochs can indeed help in improving the classification accuracy. Hence, we included standard deviation of each epoch as a feature along with the descriptors derived from PP. Since EEG has both long-term and short-term correlations

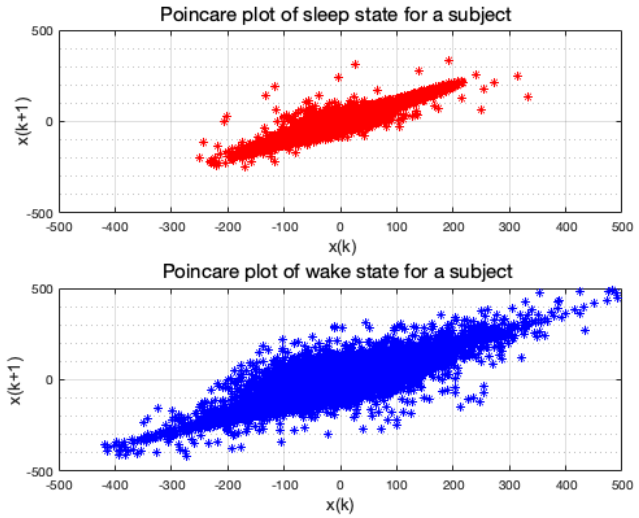

Fig. 1. Example illustration of Poincaré plots for sleep and wake states of a subject from the DREAMS-Subjects database.

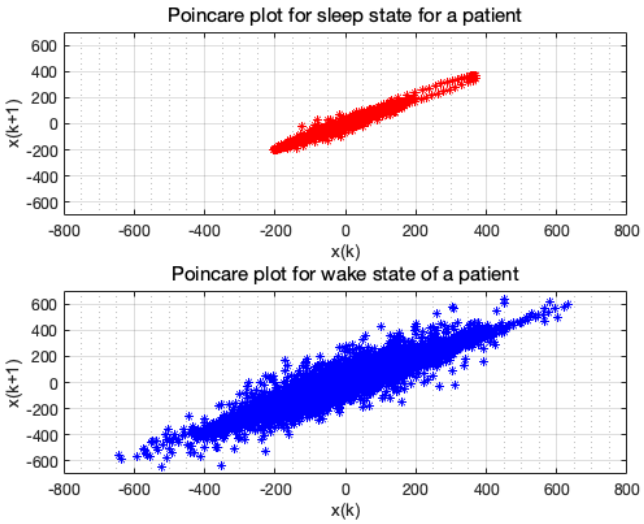

Fig. 2. Example illustration of Poincaré plots for sleep and wake states of a patient with mixed apnea from the DREAMS-Patients database.

at different time scales, a delayed PP approach suggested in [12] is also used in our work. Instead of using consecutive samples (i.e., with lag of 1), we used multiple lags (varied from 1 to 100) and for each such lag, constructed a PP and computed energy of the waveforms generated by the slopes and intercepts (E_S and E_O) of linear fit on the lagged Poincaré plots. These energy values seem to provide a good distinction between sleep and wake states with higher energy in the wake than the sleep state.

Further, a novel descriptor called complex correlation measure (CCM) proposed in [14] to quantify the temporal information of Poincaré plot is also utilized in this work. CCM measures the sum of the areas of triangle formed by three consecutive points in a moving window across the Poincaré plot, thereby providing temporal variations within that window. Hence, it calculates a finer point-to-point variation which might not be captured by standard descriptors (SD1 and SD2) since they essentially capture gross overall temporal variability. All the features considered in this work are listed in Table II.

TABLE II

FEATURES CONSIDERED IN THIS STUDY.

Features	Description
SD1	Width of PP (dispersion perpendicular to the line of identity)
SD2	Length of PP (dispersion along the line of identity)
SD12	Ratio of SD1 to SD2
SD	Standard deviation of epoch
S	Area of PP ($\pi \times SD1 \times SD2$)
CCM	Complex correlation measure of PP
E_S	Energy of the slopes of multiple lagged PP
E_O	Energy of the offsets of multiple lagged PP

2) Classification: The classifier used in this study is RUSBoost, which is an ensemble of decision trees along with random undersampling [22]. The reason to choose RUSBoost classifier is that it is able to tackle the problem of class-imbalance by undersampling the majority class, thus providing a balanced dataset for classification. The different hyperparameters of RUSBoost are the number of weak learners (trees), learning rate, and maximum number of splits for each tree. The values are chosen to be 2000 weak learners, with learning rate of 0.1 and maximum splits equal to the number of training samples. These values are fine-tuned by using a grid search across a range of values for each of these hyperparameters.

The statistical significance of the features is tested by Kruskal-Wallis test, a non-parametric version of one-way ANOVA. The $p-$values for each dataset is listed in Table III. It can be seen that all the eight features are statistically significant with $p-$value less than 0.005. The performance of the proposed method is evaluated using 50%-holdout and 10-fold crossvalidation techniques. In 50% hold-out method, half of the total number of subjects available in a dataset are used for training, and the remaining for testing. This is repeated for 10 different runs, each run randomly selecting the training and test subjects. In 10-fold crossvalidation technique, all the subjects' data are merged and split into 10 different folds; out of which 9 folds are used for training, and the left out fold for testing. This is executed 10 times; each time one of the 10 folds is used as the test set. The final performance is reported as the average classification accuracy across the 10 folds.

III. RESULTS AND DISCUSSION

The proposed method achieves 10-fold crossvalidation accuracy of 96.0% using Cz-A1 EEG channel on DREAMS-Subjects dataset using only 8 features. The confusion matrix between the scores predicted by our method and the experts is presented in Table IV. The values in the diagonal show the number of correctly classified epochs corresponding to each state (sleep and wake). The performance metrics,

TABLE III

SIGNIFICANCE ANALYSIS (p-VALUES) USING KRUSKAL-WALLIS ONE-WAY ANOVA TEST FOR DIFFERENT DATASETS

Features	Datasets		
	DREAMS-Subjects	Sleep-EDF	DREAMS-Patients
SD	0	$0.3e-25$	0
SD2	$0.37e-13$	0	0
SD1	0	0	0
S	$0.62e-13$	0	$0.13e-45$
SD12	0	0	0
CCM	0	0	0
E_S	0	0	0
E_O	0	0	0

namely sensitivity, precision, and F1-score (harmonic mean of precision and sensitivity) are also computed. These metrics are derived from the confusion matrix as shown below.

$$Sensitivity = TP/(TP+FN) \quad (1)$$

$$Precision = TP/(TP+FP) \quad (2)$$

$$F1-score = 2TP/(2TP+FN+FP) \quad (3)$$

where TP, FP, and FN denote true positives, false positives and false negatives, respectively.

The values of these performance metrics are presented in Table V for all three datasets. For DREAMS-Subjects dataset, our method provides high sensitivity, precision and F1-score values of 97.9%, 96.9%, and 97.4% for the sleep state, while they are comparatively less (86.2%, 90.5%, and 88.3%, respectively) for the wake state. Table VI compares the classification accuracies and kappa values [23] of the proposed method with the existing literature for DREAMS-Subjects dataset. It can be seen that this approach is able to provide comparable results with a minimal set of 8 features. Furthermore, an average classification accuracy of $90.9 \pm 1.1\%$ is obtained using 50%-holdout validation technique (performance averaged over 10 runs; each run comprising 50% of the total number of subjects randomly selected for training and the rest 50% used for testing).

TABLE IV

CONFUSION MATRIX FOR 2-CLASS (SLEEP-WAKE) CLASSIFICATION USING POINCARÉ PLOTS OF A SINGLE EEG CHANNEL (CZ-A1) ON DREAMS-SUBJECTS DATASET WITH 10-FOLD CROSSVALIDATION.

		Predicted Class	
		Sleep	**Wake**
True Class	**Sleep**	24153	505
	Wake	774	4827

On DREAMS-Patients dataset, we achieved 10-fold cross-validation accuracy of 94.4% with 96.8% sensitivity, 95.6% precision, and 96.2% F1-score for the sleep stage. Also, a high kappa value of 0.86 is obtained indicating good agreement between the experts and our method. Table VII shows the confusion matrix for the patient dataset using

TABLE V

RESULTS OBTAINED ON DREAMS-PATIENTS, DREAMS-SUBJECTS, AND SLEEP-EDF DATABASES EMPLOYING 10-FOLD CROSSVALIDATION. LISTED ARE THE SENSITIVITY, PRECISION AND F1-SCORE VALUES (IN %) USING A SINGLE EEG CHANNEL.

Database	Sensitivity		Precision		F1-score	
	Sleep	Wake	Sleep	Wake	Sleep	Wake
DREAMS-Patients	96.8	88.3	95.6	91.3	96.2	89.8
DREAMS-Subjects	97.9	86.2	96.9	90.5	97.4	88.3
Sleep-EDF	98.2	98.1	97.9	98.4	98.0	98.3

10-fold crossvalidation. We obtained 50%-holdout accuracy (averaged over 10 runs) of $79.5 \pm 3.9\%$. Since none of the studies in the literature have reported the performance on DREAMS-Patients database, we could not compare the results of our method. We also evaluated the prediction accuracies for each of the patients by using the training data of only healthy subjects. The results are presented in Fig. 3 for each of the patients corresponding to various sleep disorders: PLMS, dyssomnia, mixed apnea and SAHS (one patient is not shown here as the pathological condition is not specified in the dataset). It is evident from the figure that the proposed method is able to provide good classification accuracies for the unseen test data of patients group. Figure 4 presents the actual hypnogram and the hypnogram generated by the proposed method for a patient. In this case, out of 1501 epochs, 1388 epochs are correctly classified, thus providing an accuracy of 92.5%. This shows that our method is well able to predict the correct state for most of the epochs.

TABLE VI

COMPARISON OF OUR 10-FOLD CROSSVALIDATION ACCURACY (IN %) AND KAPPA VALUE WITH THE EXISTING LITERATURE FOR SLEEP-WAKE CLASSIFICATION ON THE DREAMS-SUBJECTS DATASET.

Study	MEFF-R [18]	Shen [24]	Hassan [9]	**Our Method**
Accuracy	96.5	96.2	93.3	96
Feature size	98	>80	28	8
Kappa	0.88	-	-	0.86

TABLE VII

CONFUSION MATRIX FOR 2-CLASS (SLEEP-WAKE) CLASSIFICATION USING POINCARÉ PLOTS OF A SINGLE EEG CHANNEL (CZ-A1) ON DREAMS-PATIENTS DATASET WITH 10-FOLD CROSSVALIDATION.

		Predicted Class	
		Sleep	**Wake**
True Class	**Sleep**	29106	977
	Wake	1350	10223

For Sleep-EDF dataset, sensitivity, precision, and F1-score values of 98.2%, 97.9%, and 98.0% are obtained by 10-fold crossvalidation for sleep state; and 98.1%, 98.4%, and 98.3%, respectively for the wake state. The corresponding

TABLE VIII

CONFUSION MATRIX FOR 2-CLASS (SLEEP-WAKE) CLASSIFICATION USING POINCARÉ PLOTS OF A SINGLE EEG CHANNEL (PZ-OZ) ON SLEEP-EDF DATASET WITH 10-FOLD CROSSVALIDATION.

		PREDICTED CLASS	
		Sleep	**Wake**
TRUE CLASS	**Sleep**	7006	127
	Wake	153	7902

TABLE IX

COMPARISON OF OUR 10-FOLD CROSSVALIDATION ACCURACY (IN %) AND KAPPA VALUE WITH THE EXISTING LITERATURE FOR 2-CLASS CLASSIFICATION ON THE SLEEP-EDF DATASET.

Study	MEFF-R [18]	Sharma [7]	Ronzhina [25]	**Our Method**
Accuracy	97.6	98.0	96.9	**98.2**
Kappa	0.94	0.96	-	**0.96**
Feature size	98	20	30	**8**

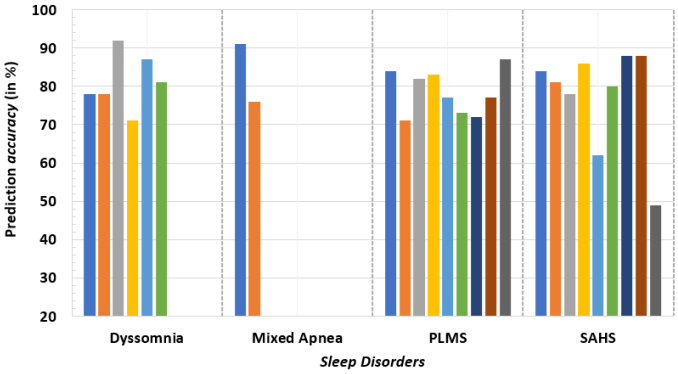

Fig. 3. Sleep-wake classification accuracies for each patient from the DREAMS-Patients dataset (N=26; Mixed apnea:2, PLMS:9, SAHS:9, Dyssomnia:6) by training the model only on healthy subjects (N=20) from the DREAMS-Subjects database.

We also found that the PP for the wake state takes a more elongated shape than for the sleep state. This observation is found to be consistent across all the control subjects as well as patients. This indicates that there is an increased level of long-term variability in the wake state. Further, we did not find any significant difference in the wake state between the two groups (healthy and patients). However, all the descriptors showed a significant difference across these two groups in the sleep state.

IV. CONCLUSIONS

This study explores the utility of Poincaré plots in sleep EEG analysis. Poincaré plot (PP) analysis has been widely used in the biomedical domain, especially for the analysis of heart rate variability and depth of anaesthesia. However, it has been less explored for sleep EEG analysis. The complexity of the brain differs between the sleep and wake states. An awake brain is more complex and chaotic than that in sleep, which we found to be well captured by the Poincaré plots. Descriptors characterizing these plots form good features to distinguish between these two states of the brain. These PP descriptors are fed as features to the RUSBoost classifier for sleep-wake classification of healthy individuals and patients with sleep disorders.

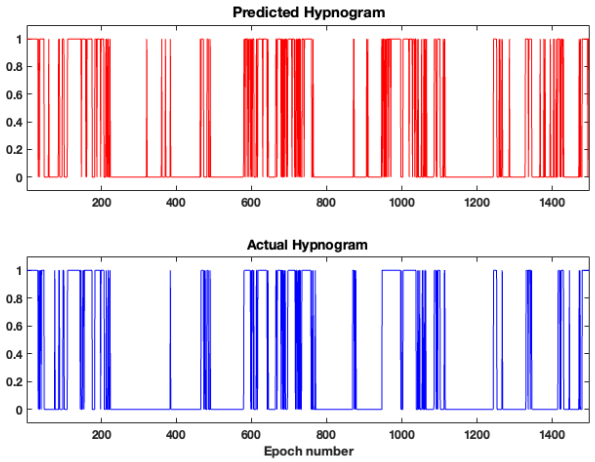

Fig. 4. Actual (blue colour) hypnogram (1:Wake; 0: Sleep) of a patient from the DRMS-PAT dataset and the hypnogram predicted (red colour) by our method.

We have utilized three different publicly available datasets to validate the performance of our method. We achieved high sensitivity values of 97.9% and 96.8% as well as high precision values of 96.9% and 95.6% for sleep stage in healthy (DREAMS-Subjects) and patient groups (DREAMS-Patients), respectively, using a single EEG channel. A high classification accuracy of 98.2% is obtained for Sleep-EDF dataset. Also, high F1-score values are obtained for all three datasets, especially for the Sleep-EDF (98% and 98.3% for sleep and wake state, respectively). Hence, the proposed method is able to provide good classification accuracies on unseen patients for sleep-wake identification by just exploiting simple features from Poincaré plots of sleep and wake states of healthy subjects. This shows its generalizability. The main advantage of PP analysis is that it does not need heavy computation, and thus is fast and efficient. Therefore, it is preferable for real-time analysis. In our future work, we would like to investigate some more properties such as symmetry and higher order Poincaré plots which may provide further improvement in the sleep-wake classification.

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