Deterministic Learning-Based WEST Syndrome Analysis and Seizure Detection on ECG

Shiyao Chen, Runze Zheng, Tianlei Wang, Tiejia Jiang, Feng Gao, Danping Wang, and Jiuwen Cao, *Senior Member, IEEE*

***Abstract*—WEST syndrome is an unknown etiology infant epilepsy, which is characterized by the flexion spastic seizure, intellectual motion development lag, electrode abnormalities, arrhythmia. In this brief, we present a novel electrocardiogram (ECG) based WEST syndrome epilepsy seizure detection method. Based on deterministic learning (DT) theory, the dynamic model of ECG is firstly constructed. The cardiodynamicsgrams (CDGs) of ECGs in seizure and interictal periods are then derived. Nonlinear features on CDGs are extracted for WEST syndrome characterization. For performance evaluation, experiments on ECGs of 12 WEST syndrome patients from the Children's Hospital of Zhejiang University School of Medicine (CHZU) is carried out. The proposed method can obtain an average of 94.49% F1-score, 93.76% precision and 95.58% accuracy, that outperforms the heart rate variability (HRV) based methods.**

***Index Terms*—WEST epilepsy syndrome, ECG, seizure detection, heart rate variability, infantile spasms.**

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Shiyao Chen, Runze Zheng, and Tianlei Wang are with the Machine Learning and I-Health International Cooperation Base of Zhejiang Province and the Artificial Intelligence Institute, Hangzhou Dianzi University, Hangzhou 310018, China (e-mail: csy_9716@163.com; runzewuyu@hdu.edu.cn; tianleiwang@hdu.edu.cn).

Tiejia Jiang and Feng Gao are with the Department of Neurology, The Children's Hospital, Zhejiang University School of Medicine, National Clinical Research Center for Child Health, Hangzhou 310003, China (e-mail: jiangyouze@zju.edu.cn; epilepsy@zju.edu.cn).

Danping Wang is with the Machine Learning and I-Health International Cooperation Base of Zhejiang Province and the Artificial Intelligence Institute, Hangzhou Dianzi University, Hangzhou 310018, China, and also with the Plateforme Sensorimotricité, BioMedTech Facilities INSERM US36-CNRS UMS2009, Université de Paris, 75270 Paris, France (e-mail: danping.wang@parisdescartes.fr).

Jiuwen Cao is with the Machine Learning and I-Health International Cooperation Base of Zhejiang Province and the Artificial Intelligence Institute, Hangzhou Dianzi University, Hangzhou 310018, China, and also with the Research Center for Intelligent Sensing, Zhejiang Lab, Hangzhou 311100, China (e-mail: jwcao@hdu.edu.cn).

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I. Introduction

WEST epilepsy syndrome, known as infantile spasm, has complex etiology and unknown mechanism. It is characterized by decreased intellectual development and arrhythmia. Most children have seizures within one year after birth, with peak incidence occurring between 3-8 months. More than half of WEST syndrome subjects will evolve into other epilepsy syndromes, such as Lennox-Gastaut syndrome [1]. About 50% patients have movement disorders and 70% suffer from intellectual disability, usually accompanied by mental and behavioral problems, such as autism and hyperactivity. Electroencephalogram (EEG) is most effective in epilepsy analysis [2]–[6], but is inconvenient in acquisition.

Electrocardiogram (ECG) became favorable in epilepsy analysis in recent years. WEST syndrome affects the autonomic nervous system (ANS) with the accelerated tachycardia [7]. In [8], the fused features on EEG and ECG have been studied for WEST and childhood absence epilepsy (CAE) syndrome classification. An early seizure detection method for WEST syndrome based on cardiac autonomic regulation dynamics has been developed in [9]. It is recently shown that [10] WEST syndrome subjects apparently have an increased prevalence of cardio metabolic derangement. Although fruitful results have been done on ECG based epilepsy analysis, most are using heart rate variability (HRV). The essence of the heart as a nonlinear dynamic system is usually ignored.

As an effective and accurate modeling method for unknown dynamical nonlinear systems with periodic or regression trajectories, deterministic learning (DT) [11] has been successfully applied in myocardial ischemia of ECG [12], [13]. Inspired by DT, we present a novel WEST epilepsy syndrome analysis and seizure detection method in this brief. A high-gain observer (HGO) [14] is firstly adopted to estimate the ECG signal velocity and acceleration states, which are more effective in characterizing the instantaneous change of ECGs [15]. Then, the ECG cardiodynamicsgram (CDG) is derived based on DT. Further, popular nonlinear features are extracted from CDGs for WEST syndrome epilepsy characterization and seizure detection. The contributions of this brief are threefold:

- The DT method is firstly applied on ECGs of WEST syndrome for epilepsy detection through CDG features.
- A HGO is adopted for velocity and acceleration estimation to effective characterize the instantaneous change.

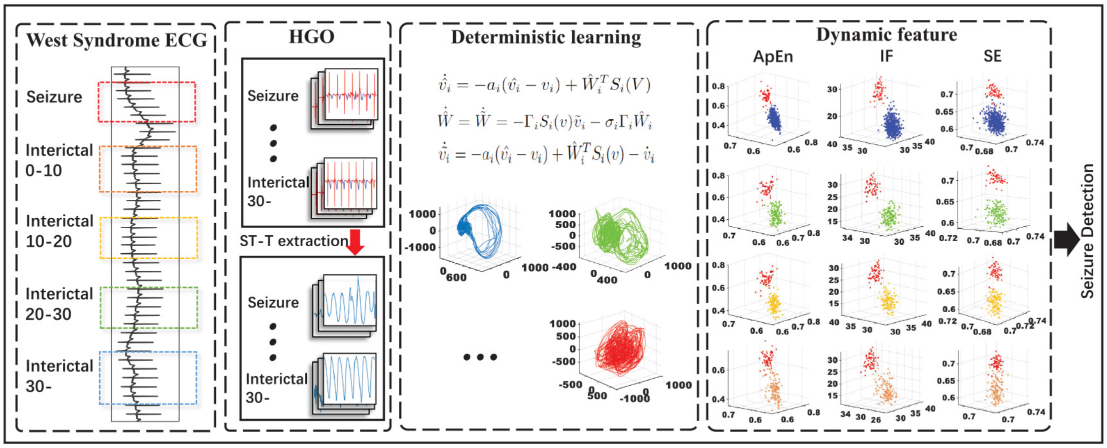


Fig. 1. WEST syndrome epilepsy analysis and seizure detection using ECG based deterministic learning algorithm.

- Nonlinear features on CDG are derived to achieve WEST seizure detection using machine learning method.

Experiments conducted on ECGs of 12 WEST syndrome children recorded in children's Hospital of Zhejiang University (CHZU) are provided to show the advantage of our method.

II. Proposed DT Based WEST Syndrome Analysis

Fig. 1 shows the structure of the proposed WEST syndrome seizure detection algorithm. Firstly, a HGO is adopted on single lead ECG to estimate the velocity and acceleration for deriving the dynamic system. Then, the cardiac dynamics extracted from ST-T ECG segments is used in DT algorithm to build the CDGs of ECGs. Finally, the approximation entropy (ApEn), spectral entropy (SE), instantaneous frequency (IF), are taken from CDGs for epilepsy characterization and detection.

A. High-Gain Observer

Dynamic pattern extraction in ECGs is always challenging. Since human heart is extremely complex, identifying its dynamics becomes vital. It is pointed out [14] that any dissipative systems can be approximated by a 3-dimensional ordinary differential function with arbitrary accuracy, providing a way for ECG dynamics analysis. Based on DT, the cardiac dynamics of ECG for myocardial ischemia has been analyzed [16].

To effectively characterize the instantaneous change of ECGs, we recur to using HGO [16] to estimate the ECGs' velocity and acceleration [17], [18]. As an effective state estimation method, HGO is robust to model disturbances and uncertainties, and can estimate the derivative of the output robustly with a rapid convergence. After filtering by a median filter, a 50 Hz notch filter and 0.5-70 Hz bandpass filter, HGO is employed for ECG dynamics modeling. Particularly, the velocity and acceleration estimation is performed below.

The discrete-time HGO design [19] is

$$\begin{aligned} q(k+1) &= A_{\mathrm{d}} q(k) + B_{\mathrm{d}} y(k) \\ \hat{x}(k) &= C_{\mathrm{d}} q(k) + D_{\mathrm{d}} y(k), \end{aligned} \tag{1}$$

where $y(k)$ is the ECG, $q(k)$ is the state vector and $\hat{x}(k)$ is the estimated ECG. Here, the bilinear transformation method is applied for implementation, with $A_{\mathrm{d}} = (I + (\alpha/2)A_o)(I - (\alpha/2)A_o)^{-1}$, $B_{\mathrm{d}} = \alpha(I - (\alpha/2)A_o)^{-1}H_o$, $C_{\mathrm{d}} = D^{-1}(I - (\alpha/2)A_o)^{-1}$, $D_{\mathrm{d}} = (\alpha/2)C_{\mathrm{do}}H_o$, $D = diag[1, \varepsilon, \ldots, \varepsilon^{n-1}]$, $H_o = [h_1, h_2, \ldots, h_n]^T$, $A_o = A - H_oC$, and $\alpha = Ts/\varepsilon$. Here, I is the identity matrix, $Ts = 1000$ Hz is the ECG sampling frequency, $\alpha = 1$, $\varepsilon = 1000$, and

$$\begin{aligned} A_0 &= \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix}, B_0 = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \\ C_0 &= \begin{pmatrix} 0 \; 0 \; 1 \end{pmatrix}, D_0 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1000 & 0 \\ 0 & 0 & 1000^2 \end{pmatrix} \end{aligned} \tag{2}$$

It is shown [19] that when the observer gain and sampling frequency are large enough, $\hat{x}(k)$ can converge to a small enough neighborhood. With the estimated velocity and acceleration, the ST-T segments will be obtained from the 3-lead signal as they are more effective in describing myocardial ischemia. As shown in [20], myocardial ischemia also exists in children with epilepsy.

The ECG R wave is determined by a dynamic threshold as

$$\begin{aligned} SR(i) &= [R(i), R(i+1)], i = 1, \ldots, N-1 \\ Range(i) &= [R(i) + \alpha, \frac{SR(i) + SR(i+1)}{2}], \end{aligned} \tag{3}$$

where N and R are the R wave number and position, α is a dynamic threshold.

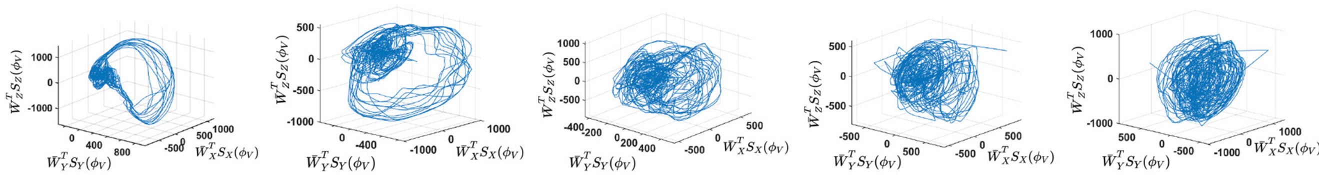
B. Deterministic Learning

Deterministic learning theory (DT) [16], [21] has been developed for dynamic system modeling with promising achievements in many applications. Based on the persistent excitation (PE) of radial basis function (RBF) neural network, it is proved that local RBF can be used as the parameterized model to accurately model unknown nonlinear system.

Assume the model of a periodic or regression trajectory [12] is

$$\dot{x} = F(x; p), x(t_0) = x_0, \tag{4}$$

where $x = [x_1, \ldots, x_n]^{\mathrm{T}} \in R^n$ is the system state, p is a constant system parameter vector, and



(a) interictal (30 m above) (b) interictal (20-30 m) (c) interictal (10-20 m) (d) interictal (0-10 m) (e) seizure period

Fig. 2. CDGs of different periods of WEST epilepsy syndrome (m: minutes).

$F(x; p) = [f_1(x; p), \ldots, f_n(x; p)]^{\mathrm{T}}$ is the continuous unknown nonlinear function. The trajectory initial point x_0 is expressed as ϕ_ζ, either a periodic or a recurrent motion. To estimate $F(x; p)$, the estimator of RBF neural network in DT [12] is

$$\dot{\hat{x}}_i = -a_i(\hat{x}_i - x_i) + \hat{W}_i^T S_i(x), \tag{5}$$

where $\hat{x}$ and x_i are the estimator and system states, $a_i > 0$ is a constant, and $\hat{W}_i^T S_i(x)$ is used to approximate $f_i(x; p)$ of (4) with $\hat{W}_i = [w_{i1}, \ldots, w_{iN}]^T \in R^N$ and $S_i(x) = [s_{i1}(\|x - \xi_1\|), \ldots, s_{iN}(\|x - \xi_N\|)]^T$, $s_{ij}(\cdot)$ being the Gaussian function and ξ_j being different points in state space.

With (4) and (5), the derivative of the state estimation error $\tilde{x}_i = \hat{x}_i - x_i$ satisfies [12]

$$\begin{aligned} \dot{\tilde{x}}_i &= -a_i\tilde{x}_i + \hat{W}_i^T S_i(x) - f_i(x; p) \\ &= -a_i\tilde{x}_i + \hat{W}_i^T S_i(x) - \varepsilon_i, \end{aligned} \tag{6}$$

where $\varepsilon_i = f_i(x; p) - {W_i}^{T*} S_i(x)$ is the ideal approximation error and $\tilde{W}_i = \hat{W}_i - {W_i}^*$. Then, $\hat{W}_i^T$ [12] can be updated by

$$\dot{\hat{W}}_i = \dot{\tilde{W}}_i = -\Gamma_i S_i(x)\tilde{x}_i - \sigma_i \Gamma_i \hat{W}_i, \tag{7}$$

where Γ_i is the set positive learning gain, and $\sigma_i > 0$ is a small constant. Setting $\hat{W}_i(0) = 0$, it has been shown in DT that for almost every trajectory model ϕ_ζ, accurate modeling of the unknown dynamics $f_i(x; p)$ can be achieved along ϕ_ζ [12]

$$f_i(\phi_\zeta; p) = \hat{W}_i^T S_i(\phi_\zeta) + \varepsilon_{\zeta i} = \bar{W}_i^T S_i(\phi_\zeta) + \varepsilon_{\zeta i1}, \tag{8}$$

where $\bar{W}_\zeta = \mathrm{mean}_{t \in [t_a, t_b]} \hat{W}_\zeta(t)$ is the arithmetic mean, $0 < t_a < t_b$ is the period after the transient process and $\varepsilon_{\zeta i1} = O(\varepsilon_{\zeta i}) = O(\varepsilon_i)$ is the approximation error.

In this brief, the ECG dynamic is modeled [12] using the ST-T segments as

$$\dot{V} = F(V), \tag{9}$$

where $V = [v_X, v_Y, v_Z]^{\mathrm{T}}$ represents the ECG and its velocity, acceleration obtained by HGO, $F(V) = [f_X(V), f_Y(V), f_Z(V)]^{\mathrm{T}}$ is the CDGs underlying the 3D pattern ϕ_V. Based on DT theory, $(i \in \{X, Y, Z\})$, the CDGs $f_i(V)(i \in \{X, Y, Z\})$ can be accurately estimated using 3 RBF networks $\hat{W}_i^T S_i(\phi_\zeta)$.

Fig. 2 shows the ECG CDGs of 5 different periods, namely seizure onset, interictal periods with 0-10, 10-20, 20-30, more than 30 minutes from seizure onset of a WEST epilepsy subject. As clearly observed, 1) the CDG morphology of ECG in interictal stage with 30 minutes away from epilepsy seizure shows a regular curve, 2) the CDG morphology becomes messy for ECGs gradually approaching the onset period,

Algorithm 1 DT Based WEST Epilepsy ECG Learning

Input: ECG $y(i)$, α, Ts, A_{d}, B_{d}, C_{d}, D_{d}, N, α
Output: *CDG*, $\hat{x}$, *ApEn*, *IF*, *SE*

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x̂(1) = (0 0 1)
q(1) = C_d^{-1}(x(1)^T − D_d y(1))
for k = 1 to N do
    x̂(k) = C_d q(k) + D_d y(k)
    q(k + 1) = A_d q(k) + B_d y(k)
end for
for i = 1 to N do
    mean(i) = (R(i) + R(i + 1))/2
    Range(i) = [R(i) + α, mean(i)]
end for
dx̂_i/dt = −a_i(x̂_i − x_i) + Ŵ_i^T S_i(x)
dx̂/dt ⇒ Obtain CDG based ApEn, IF and SE
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3) The closer to seizure, the more cluttered CDG morphology curves will be.

C. Dynamic Feature Extraction

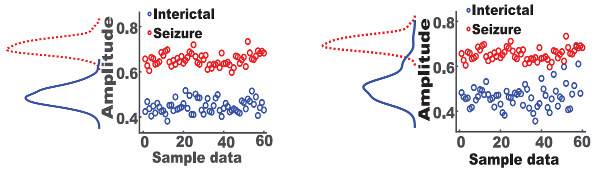
To further characterize CDGs, 3 popular nonlinear features, approximation entropy (ApEn), spectral entropy (SE), instantaneous frequency (IF), are extracted. ApEn reflects the stability and regularity of a signal. SE measures the spectral power distribution of a signal. Instantaneous frequency (IF) is generally more effective than conventional Fourier transform in representing non-stationary signals. The unique instantaneous effectiveness of IF in depicting non-steady signal makes it promising to extract the local pattern.

Figs. 3∼5 show the scatter plots and probability density distributions (PDFs) of ApEn, SE and IF, respectively. For each figure, the comparisons are made between ECGs of seizure and 2 different interictal periods of WEST syndrome. As observed, for all 3 dynamic features, there have clear distribution differences between seizure vs two interictal periods, making them discriminative in characterizing WEST syndrome. Algorithm 1 briefly summarizes the proposed WEST epilepsy seizure detection algorithm.

III. Results and Analysis

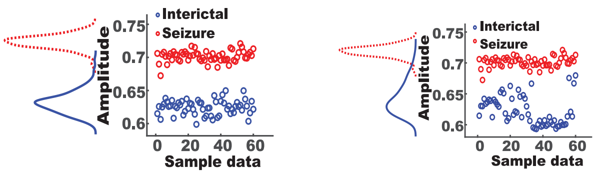
A. Experiment Setups

To study the effectiveness of our proposed method, we adopt popular machine learning algorithms for performance evaluation [22], [23], including Long short-term memory (LSTM),



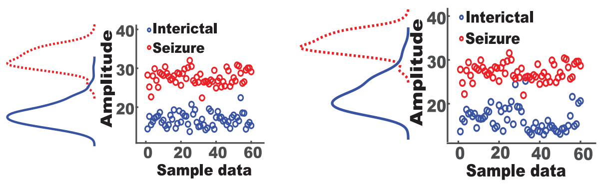
(a) vs interictal 30 m above (b) vs interictal (0-10 m)

Fig. 3. Comparisons of ECG ApEn in seizure vs interictal.



(a) vs interictal 30 m above (b) vs interictal (0-10 m)

Fig. 4. Comparisons of ECG SE in seizure vs interictal.



(a) vs interictal 30 m above (b) vs interictal (0-10 m)

Fig. 5. Comparisons of ECG IF in seizure vs interictal.

K-Nearest Neighbor (KNN), support vector machine (SVM) and Random Forest (RF). For KNN, the nearest neighbor is set to be 8. In SVM, the linear kernel is used, with C = 2, sigma = 3. For RF, 80 decision trees are used. For LSTM, the neural network with the bi-directional structure is applied, and at each time step, the input feature dimensions are 3.

Besides the proposed CDGs nonlinear features, we also compare with the ECG HRV features. For HRV, 8 time-domain, 7 frequency-domain and 4 nonlinear features are derived, including the standard deviation of RR intervals, the standard deviation of successive RR intervals, the square root of the mean squared differences between successive RR intervals, the mean of between successive RR intervals, the quartiles of RR intervals, the coefficient of variation, the number of successive RR intervals over 50 ms, the ratio of successive RR intervals over 50 ms, the power spectrum of very low frequency (0.03-0.04 Hz), low frequency (LF, 0.04-0.15 Hz), high frequency (HF, 0.15-0.4 Hz), LF/HF, the total power of all frequency bands (TP), the norms of LF (LF-norm) and HF (HF-norm), the standard derivation (SD) of Poincare curve of RR interval, SD1 (rapid beat-to-beat changes), SD2 (long-term beat-to-beat changes), and SD1/SD2 are also obtained.

For feature extraction, the frame length of ECG is set to be 8 s with 50% overlap. Tables I and II show the dataset specifications, and the detailed training and testing samples of all subjects. The ECGs are collected by Nicolet V32 amplifier with 1000 Hz sampling frequency. All data are labeled by neuroscientists of CHZU. The experiments are conducted under the scenario by identifying seizure to different interictal periods. For performance evaluation, accuracy, precision and F1-score are calculated using the 5-fold cross-validation.

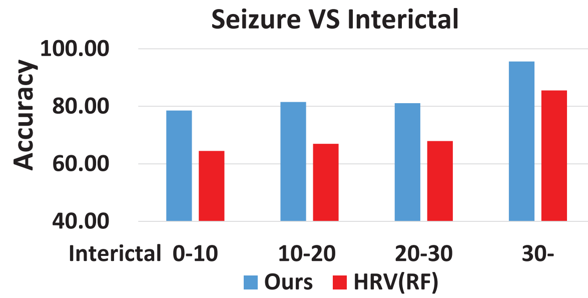


Fig. 6. Detection results comparing with ECG HRV features.

TABLE I
SPECIFICATIONS OF CHZU DATASET

ID	Gender	Age	Seizure number	seizure time (s)
1	F	1y8m	5	272
2	M	10m17d	3	180
3	F	9m1d	5	272
4	M	unknown	8	464
5	F	1y1m	6	328
6	F	6m17d	9	500
7	F	7m8d	10	572
8	F	1y9m	2	92
9	F	2y10d	13	740
10	F	2y1m	4	240
11	F	8m27d	5	252
12	M	unknown	4	228

TABLE II
SAMPLES IN CHZU WEST SYNDROME DATASET

category	**seizure**	**interictal**			
		0-10	**10-20**	**20-30**	**30 above**
Training	851	1161	1072	845	2337
Testing	213	291	269	212	585

B. Results and Discussion

1) Results by CDG Nonlinear Features: Table III shows the detailed epilepsy detection results by ECG CDGs nonlinear features obtained by our method. As observed, 1) among these 4 classifiers, LSTM always achieves the best performance, 2) with CDG nonlinear features, LSTM can obtain 95.58% accuracy when comparing seizure with the interictal period (30 m above), 3) among 4 different scenarios, the performance gradually becomes better when the interictal period is far away from the seizure onset.

2) Comparisons With HRV Features: Fig. 6 shows the detection performance comparison with ECG HRV features. In our proposed method, we use LSTM with CDG nonlinear features, while for HRV, the classifier with the best performance is presented, namely RF. As observed, CDG nonlinear features extracted by DT algorithm on ECGs are more discriminate than HRV features in characterizing WEST syndrome. The poor performance of HRV could attribute to the feature depending on subject's heart rate, which can be easily interfered as WEST syndrome subjects are usually infants.

TABLE III
RESULTS BY CDG NONLINEAR FEATURE

	LSTM	RF	SVM	KNN
	seizure vs interictal (0-10 m)			
Accuracy	**78.55**	64.10	74.75	73.82
Precison	**78.61**	64.11	74.78	73.23
F1-score	**78.27**	61.59	73.29	72.89
	seizure vs interictal (10-20 m)			
Accuracy	**81.51**	64.13	74.81	74.71
Precison	**83.03**	63.71	74.71	74.33
F1-score	**82.54**	62.64	74.06	74.33
	seizure vs interictal (20-30 m)			
Accuracy	**81.10**	75.71	67.81	75.71
Precison	**82.15**	75.74	68.18	75.75
F1-score	**80.18**	75.70	67.53	75.65
	seizure vs interictal (30 m above)			
Accuracy	**95.58**	90.14	84.65	88.28
Precison	**93.76**	87.55	83.90	86.10
F1-score	**94.49**	86.97	77.64	84.40

IV. CONCLUSION

This brief presents a novel ECG based WEST syndrome epilepsy analysis and seizure detection method. Applying deterministic learning, the cardiodynamicsgram morphology of ECG signal is built. The dynamic nonlinear features extracted on CDG can effectively characterize the dynamics of WEST epilepsy ECGs in seizure and interictal periods. The superiority of detection performance is validated using ECGs of 12 WEST syndrome subjects. The research results open up a new door for epilepsy syndrome and seizure detection with ECG signals using deterministic learning theory. In the future, to reduce the false detection rate in the interictal period closer to onset, more types of nonlinear features will be explored. At the same time, the specificity of the algorithm will be studied to exploit the applicability in real applications.

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