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ECG Denoising using a Single-Node Dynamic Reservoir Computing Architecture

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KEYWORDS:
Electrocardiogram, Reservoir Computing, Denoising, Single node reservoir computing

***Abstract*—Accurate detection of heart disease requires purely realistic electrocardiogram (ECG) signals. In the process of acquisition and transmission, various noises destroy the clean ECG signal, making diagnosis difficult. Here, we apply a single node Reservoir computing (SNRC) architecture based on a recurrent neural network (RNN) to solve this problem by minimizing typical electromyogram noise (EMG) and power line interference (PLI) that damage the ECG signal. MIT-BIH, the standard online arrhythmia database, is used to collect data and test the quality of the proposed method. To evaluate the SNRC architecture, we use two performance indicators, namely, SNR output improvement (SNRimp) and the Percentage Root mean square Difference (PRD). The proposed SNRC architecture is superior to the latest technology and can achieve higher SNRimp and lower PRD for all types of typical ECG noise under study. These results indicate that the proposed SNRC architecture is expected to efficiently restore the dynamics of ECG signals in vivo.**

I. INTRODUCTION

As a result of cardiovascular diseases, a huge number of deaths around the world occurs; around 31% of all deaths in the world [1]. According to the World Health Organization (WHO) [2], "Arrhythmia is the principal reason for the significant number of cardiovascular disease deaths". Electrocardiography (ECG) is a test that measures and diagnoses heart rate and rhythm. To avoid wasting information about the electrical activity of the heart and to make diagnosis simple and accurate, we need to keep the ECG signal clean and noise-free. But, in fact, the real situation is the opposite. When ECG signals are sent to healthcare facilities from non-clinical locations such as homes and airplanes, if the communication channel is not efficient enough, the received ECG will be destroyed. Various types of noise can destroy ECG signals, such as abrupt changes in baseline**,** Baseline Drift (BW), Muscle Artifacts (MA), Power Line Interference (PLI), Additive White Gaussian Noise (AWGN), and electromyogram noise (EMG) [3]. In recent years, many techniques have been used to overcome these noises that destroy ECG signals.

In 2004, ERGUN proposed the Discrete Wavelet Transform (DWT) technology [4], which is used to remove noise from ECG signals. This technique is based on the second-generation wavelet transform and a level-dependent threshold estimator. However, wavelet-based filters cannot preserve edges properly.

Three years later, Reza used the extended Kalman filter (EKF) technology [5]. EKF is a non-linear version of the Kalman filter, which can linearize the current mean and the covariance estimates. However, if the initial state estimate is

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incorrect or the process is modeled incorrectly, the filter can quickly diverge.

Blanco [6] decomposed the signal into the sum of the intrinsic mode function (IMF) in 2008. The IMF is defined as a function that has the same number of extreme values and its envelope is zero. As defined by all local maxima and minima, this function is symmetric around zero. However, when a window is applied to preserve the QRS complex in the low-order IMF, the noise component will remain in the QRS area.

In 2016, DWT with Adaptive Dual Threshold Filter (ADTF) technology was used [7]. The algorithm is based on three denoising steps, namely DWT decomposition, ADTF step, and highest peak correction. However, ADTF rejects the initial sub-band of the wavelet decay signal, causing a great deal of information loss in the higher frequency region. Also, for peak correction, it uses a single amplitude threshold, which may not be able to detect peaks correctly for QRS patterns and abnormal ECG conditions that change over time.

In 2018, a technique combining empirical mode decomposition (EMD) and the adaptive switching mean filter (ASMF) was proposed [8]. Using this technique, Rakshit and Das adopted a wave-based soft threshold scheme to reduce the high-frequency noise of the ECG in the signal. Then, they use ASMF operations to minimize low-frequency noise.

More recently, Md-Billal [9] used variable frequency composite Demodulation (VFCDM) to remove the sub-band decomposition of noise-contaminated ECG signals. Tracey and Miller used a non-local mean (NLM) method for ECG denoising [10].

In this paper, we propose a Single Node Reservoir Computing (SNRC) architecture with an integrated cumulative mean filter [11]. We investigate two typical noise types, i.e., EMG, and PLI, as they are the most disturbing noise sources in biopotential recordings that hamper the analysis of the electrical signals generated by the human body. The EMG noise is generated from the electrical activity of the muscle. EMG consists of a maximum frequency of 10 KHz. On the other hand, the powerline interference (PLI) includes the fundamental PLI component of 50 Hz/60 Hz and its harmonics. As far as we know, we are the first team to introduce SNRC to eliminate ECG noise. The dynamic behavior of SNRC shows the ability to reduce ECG noise and recover components of the ECG signal. Furthermore, the introduced technique filters damaged ECG signals with high performance that exceeds the performance of existing related techniques. The rest of this article is organized as follows. Section II presents the related methods to RC. Section III illustrates the details of the proposed SNSR denoising technique. Section IV presents the results and related discussions. Finally, the fourth section summarizes the paper.

II. RELATED METHODS TO RC

Reservoir Computing (RC) is based on the Recurrent Neural Networks (RNN), which provides a greatly improved ability to process time data compared to traditional feedback neural networks. Due to the cyclic connections among hidden neurons, which are absent from feedforward neural networks, outputs in the RNNs depend on both the current inputs and the neurons' previous states, so that the RNN can find the time correlation in the data.

Reservoir Computing (RC) consists of three layers: the input layer, the reservoir, and the output layer. The input layer allows the input signal to enter the reservoir through a fixed random weighted connection. The reservoir is a series of non-linear nodes that form a recurrent neural network (RNN). With this RNN, we do not have to waste time and hardware on the gradient descent RNN training. The connections between the Reservoir outputs (states) and the output layer are the only connections that require training.

RC is suitable for many applications, such as temporal signal processing [12], brain-inspired biosignal classification [13]**,** the recognition of noisy images [14], attack detection of smart grids with wind power generators [15], the reduction of the phase sensitivity of lasers [16], the classification of dynamic patterns [17], control a simulated robot arm by LSM [18], model an existing robot controller [19], and object tracking and motion prediction [20, 21]. Furthermore, it also has applications in the field of digital signal processing (DSP), such as voice recognition [22, 23, 24] and ECG classification [25]. Concerning noise reduction applications, it has been used for noise-robust image recognition [26] and feature enhancement [27]. Jalalvand et al. [27] created a fully convolutional Denoising Auto-Encoder (DAE) system by means of an RC-network, incorporating one unidirectional reservoir. Their developed DAE system was trained using clean version of the noisy speech feature vectors for feature enhancement.

The main motivation for using RC is that it can handle a large amount of dynamic sequence information, such as the case of ECG signals. Here, Single Node Reservoir Calculation is discussed (SNRC). SNRC is a miniature version of traditional RC. Single node reservoir calculation (SNRC) is an RC, where the nonlinear node in RC is replaced with a single nonlinear node affected by delayed feedback. Dynamic memory enables SNRC to perfectly filter out noisy ECG signals.

III. PROPOSED ALGORITHM

A. *Single Node Reservoir Computing (SNRC)*

SNRC [11] is a recurrent neural network (RNN) in a shortened architecture that composes of three layers: the input layer, the reservoir, and the output layer, as shown in Fig.1. The Reservoir is a delayed feedback system that comprises a nonlinear node and a delay line of N virtual nodes. Each virtual node delays the output of the nonlinear node by a delay unit of time $\theta = \tau/N$, performing a total line delay of τ.

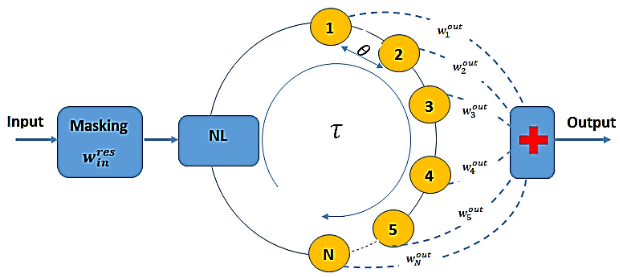

Fig .1. Single Node Reservoir Computing (SNRC) architecture

In the input layer, the discrete input signal $U(k)$, where K is the number of samples and k is a non-negative integer, $k = 0,1,2,..,K$-1, enters a sample and hold operation to generate a continuous step function $I(t)$, where $I(t) = U(k)$ for $\tau k \leq t < \tau(k+1)$, where t points to the continuous-time variable. Therefore $I(t)$ is constant over each τ, and updates its value after each new input sample. The stream $I(t)$ is further multiplied by a mask function $M(t)$, as in Fig.1 to generate $J(t)$, as follows:

$$J(t) = I(t) \cdot M(t) \quad (1)$$

Where the signal $J(t)$ is a step function that remains constant during each duration θ. The mask function $M(t)$ represents the weight vector $w_{in,i}^{res}$, where i is the index of a virtual node, $i \in \{1, N\}$. w_{in}^{res} is the weight vector between the input and the N virtual nodes and $w_{in,i}^{res}$ is the individual weight for the virtual node i. An intrinsic time T is selected, such as $\theta \lesssim T \ll \tau$, where T is the characteristic time scale of the nonlinear dynamical node. All times with are normalized for the intrinsic time scale T of the nonlinear system. For simplicity, $T = 1$. The nonlinear reservoir delay differential equations (DDE) are as follows:

$$x'(t) = -x(t) + F[x(t-\tau), J(t)] \quad (2)$$

where $F(.)$ is a nonlinear function and $x(t)$ is the output state of the nonlinear node. Assuming that $F[x(t-\tau), J(t)]$ is constant during each duration θ, after solving Eq. (2), we get:

$$x(t) = x_0 e^{-t} + (1 - e^{-t})\, F[x(t-\tau), J(t)] \quad (3)$$

where, x_0 is the initial value of the previous virtual node at beginning of each interval θ. The output states of virtual nodes $x(t)$ are found by the substitution of $t = \theta$. Now by (4), the state of the i^{th} virtual node($i \in [1, N]$), denoted by $x_{i,k}$, is recursively calculated, as a function of the input at the same time step k and the virtual node states at a time step $k - 1$. The input to a virtual node i at time step k equals $w_{in,i} U_k$.

$$x_{1,k} = x_{N,k-1} e^{-\theta} + \left(1 - e^{-\theta}\right) F(x_{1,k-1} w_{in,1} U_k)$$

$$x_{i,k} = x_{i-1,k} e^{-\theta} + \left(1 - e^{-\theta}\right) F(x_{i,k-1} w_{in,i} U_k) \quad (4)$$

$$x_{N,k} = x_{N-1,k} e^{-\theta} + \left(1 - e^{-\theta}\right) F(x_{N,k-1} w_{in,N} U_k)$$

The predicted output $\hat{y}$ is estimated by summing the weighted states in the output layer, as follows:

$$\hat{y}(k) = \sum_{i=1}^{N} w_i . x[k\tau - \frac{\tau}{N}(N - i)] \quad (5)$$

Where w_i is the i^{th} weight from the virtual node i^{th} to the output layer and $\hat{y}$ is the calculated prediction of the target.

The values of the weight vector W, composed of the individual weights w_i, $i \in \{1, N+1\}$, are computed by minimizing the mean square error between the predicted output $\hat{y}$ and the desired output, y, i.e., $min(\| WS - y \|^2)$, using a linear training algorithm, where S is the (N+1) × K state/bias matrix (i.e., the $N \times K$ state matrix (X), concatenated with the $1 \times K$ bias vector, for N nodes and K time steps). Therefore, W can be obtained by the following equation:

$$W = (yS^{\dagger})^T \quad (6)$$

Where † denotes the Moore-Penrose pseudo-inverse. More about the SNRC can be found in [10].

B. The Cumulative Mean Filter

A mean filter follows the SNRC output for smoothing the SNRC output. Consequently, we reached a higher performance. With the mean filter, the recent sample value is predicted by averaging the three values of the previous sample, the recent sample, and the following one, as shown in Fig.2. This filter is used to improve the ECG signal.

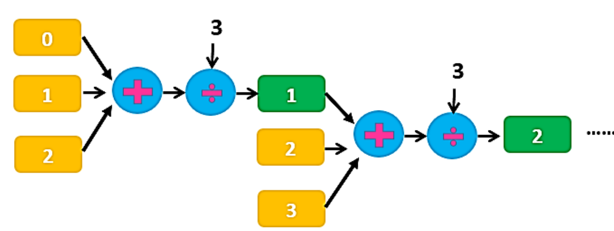

Fig .2. Cumulative Mean Filter sketch

C. Performance Metrics

Output SNR improvement (SNRimp) and percentage root mean square difference (PRD) are the two performance metrics that we employ here to compare our methodology with other previous techniques. They can be expressed as follows:

$$SNR_{imp} = 10log_{10} \frac{\sum_{n=1}^{L}(x_{ECG}[n] - Y_{ECG}[n])^2}{\sum_{n=1}^{L}(x'_{ECG}[n] - Y_{ECG}[n])^2} \quad (7)$$

$$PRD = \sqrt{\frac{\sum_{n=1}^{L}(Y_{ECG}[n]-x'_{ECG}[n])^2}{\sum_{n=1}^{L}(Y_{ECG}^2[n])}} \quad (8)$$

Where $Y_{ECG}[n]$ denotes the clear ECG, $x_{ECG}[n]$ defines the corrupted ECG signal, $x'_{ECG}[n]$ signifies the filtered ECG signal, and L is the length of the ECG signal. The greater the output SNRimp, the better the performance attained. The lower PDR and MSE, the better the overall performance.

IV. RESULT AND DISCUSSIONS

A. Database

The MIT-BIH arrhythmia database [28] is used to evaluate the SNRC system's performance. This collection has a total of 48 ECG records, each lasting 30 minutes. All of the data utilized here is sampled at 360 samples per second per channel, with an 11-bit resolution over a 10 mV range. Only 46 records are available online with MLII signals, out of a total of 48 records.

B. Experimental setup

We simulate two types of noise, namely EMG (generated by creating random noise as in [29]) and PLI (generated by generating a sine wave with an amplitude of 0.15 and a frequency of 50 Hz, as in [30]). The SNRC architecture is tested on 8 records (100 m, 101 m, 103 m, 105 m, 115 m, 200 m, 215 m, and 230 m), following [5-9]. We randomly order them for testing. Then, we shuffle the remaining 38 records and take out the first 24 records from them for training. Finally, we get 38 records (24 records (75%) for training and 8 records (25%) for the test). We only take the first 50,000 samples that are enough to test the performance of SNRC. To generate the noisy ECG, the two noises are added with the pure ECG signals. The input to noise ratio for training (4 decibels (dB), 9 dB, 14 dB, 19dB, and 24 dB) and testing (0 decibels (dB), 5 dB, 10 dB, 15 dB, and 20 dB). We take N (number of virtual nodes in SNRC) =300, 600 for EMG noise and PLI respectively. The input weight is a random vector with a uniform distribution range from -1 to 1 and θ=0.4, 0.1 for EMG noise and PLI, respectively. These values are the best values for the SNRC to remove the ECG noises. We focus on output SNR improvement (SNRimp) and percentage root mean square difference (PRD) to evaluate our methodology. The proposed technique performance is compared with the performance of the previous techniques: Discrete Wavelet Transform (DWT) filtering [4], extended Kalman filter (EKF) technique [5], empirical mode decomposition (EMD) [6], DWT with ADTF technique [7], EMD and adaptive switching mean filter (ASMF) [8], the non-local means (NLM) [10], and variable frequency complex demodulation (VFCDM) [9] (for PLI only as VFCDM was not used for EMG noise). The proposed work results are analyzed qualitatively and quantitatively.

The introduced technique is carried out on a 1.8GHz, Intel core i5CPU with 12 GB RAM and 64-Bit Windows operating system. For simulation, MATLAB 2018a software environment is used for training, validation, and testing.

C. Qualitative analysis

Comparison results between original ECG signals, corrupted ECG signals, and the SNRC system's recovered signals are visualized in Fig. 3, and Fig. 4, for two types of contaminating noises (EMG with SNR level of 15 dB, and PLI with SNR level of 5 dB, respectively). As shown visually, the SNRC shows the ability to recover the corrupted ECG signals of different levels and types of contaminating noises, with the preservation of morphological characteristics of the processed signal, i.e., maintaining the important clinical Information.

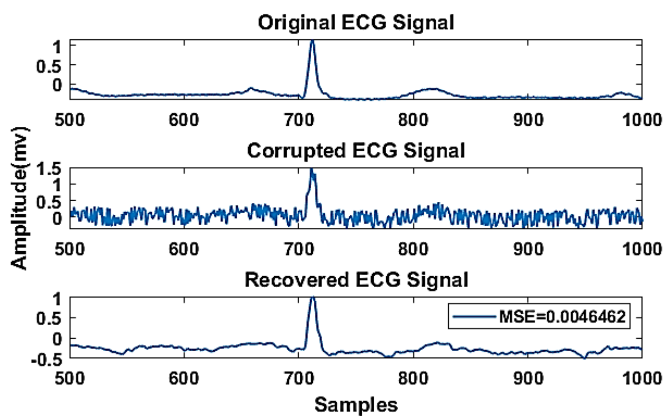

Fig. 3. Removing of EMG noise corrupted ECG signal Record101 at level SNR =15dB using the proposed SNRC system

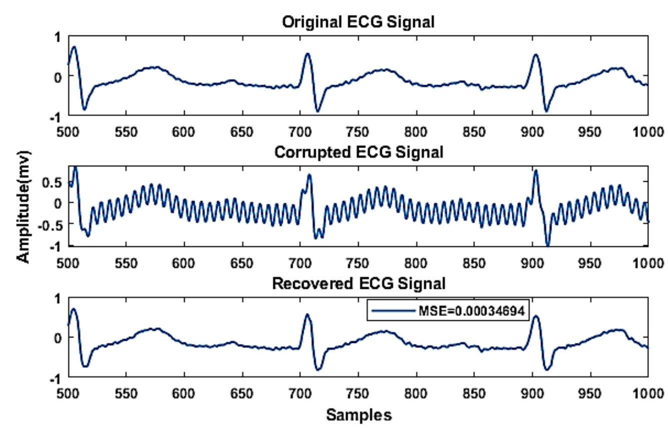

Fig. 4. Recovered of PLI noise corrupted ECG signal Record 215 at 5dB SNR

D. Quantitative analysis

To evaluate the effectiveness of the proposed technique for dynamical ECG denoising, two quantitative metrics have been evaluated, namely SNR output improvement (SNRimp) and percentage root mean square difference (PRD). Then, we compared the results to other related techniques. For each type of contaminating noise, different input SNR levels have been investigated, i.e., 0dB, 5dB, 10dB, 15dB, and 20dB. For the case of EMG contaminating noise, Table.1 illustrates the strength of the SNRC, over related methods, for ECG denoising, in terms of the different proposed metrics, i.e., SNRimp and PRD at different levels of input SNR (Table.1). As shown in the Table, the proposed technique achieves the best performance among all competing methods. For the case of PLI contaminating noise, Table.1 illustrates the strength of the SNRC, over related methods, for ECG denoising at different levels of input SNR. These results highlight the advantages and promise of the proposed technique for ECG denoising.

TABLE.1
COMPARISON RESULTS WITH RELATED METHODS

Techniques	**EMG noise**					
	level	**0**	**5**	**10**	**15**	**20**
Proposed Work	SNRimp	15.79	14.51	12.90	11.24	9.64
	PRD	24.67	15.99	10.87	7.35	4.97
EMD+ASMF [7]	SNRimp	9.298	9.13	8.78	8.05	5.67
	PRD	34.31	18.95	11.52	7.12	5.30
DWT+ADTF [5]	SNRimp	9	8.65	7.59	5.18	1.83
	PRD	37.71	20.85	13.38	10.23	8.78
EMD [4]	SNRimp	8.20	7.53	7.00	6.10	4.00
	PRD	40.12	26.57	16.87	9.58	7.68
	PLI noise					
Proposed Work	SNRimp	25	20.2	16.5	11.5	8.8
	PRD	4.2	3.8	3.8	3.2	3
VFCDM [9	SNRimp	25.13	20.42	15.55	10.60	5.65
	PRD	7.72	7.72	7.72	7.72	7.72
EMD-ASMF [7]	SNRimp	16.02	14.13	10.99	6.91	2.199
	PRD	17.005	12.36	10.04	9.27	8.50
NLM [10]	SNRimp	1.885	1.72	1.57	1.414	1.25
	PRD	63.3	37.80	23.90	14.60	8.50

V. CONCLUSIONS

We use the standard MIT-BIH arrhythmia database and simulate two types of noises, namely EMG, and PLI. For testing, we add these two noises to pure ECG signals at different SNR levels (0 decibels (dB), 5 dB, 10 dB, 15 dB, and 20 dB). Finally, we focus on output SNR improvement (SNRimp) and percentage root mean square difference (PRD) to evaluate our work. The performance of the SNRC technique outperforms the existing ECG denoising techniques. The results show the promise of using SNRC for ECG denoising.

AUTHORS CONTRIBUTION

1. Conception or design of the work: *Aya Elbedwehy and Ahmed Elnakib*
2. Data collection and tools: *Aya Elbedwehy*
3. Data analysis and interpretation: *Aya Elbedwehy*
4. Funding acquisition: **No funding received**
5. Investigation: *Aya Elbedwehy and Ahmed Elnakib*
6. Methodology: *Aya Elbedwehy and Ahmed Elnakib*
7. Project administration: *Mohy Eldin Abou-Elsoud and Ahmed Elnakib*
8. Resources: *Aya Elbedwehy and Ahmed Elnakib*
9. Software: *Aya Elbedwehy*
10. Supervision: *Mohy Eldin Abou-Elsoud and Ahmed Elnakib*
11. Drafting the article: *Aya Elbedwehy and Ahmed Elnakib*
12. Critical revision of the article: *Ahmed Elnakib*
13. Final approval of the version to be published: *Ahmed Elnakib*

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REFERENCES

[1] H. Lauri, A. Haukilahti, J. Vähätalo, T. Kenttä, H. Appel, A. Kiviniemi, L. Pakanen, H. V. Huikuri, R. J. Myerburg, and J. Junttila. Electrocardiographic associations with myocardial fibrosis among sudden cardiac death victims, Heart, 2020, http://dx.doi.org/10.1136/heartjnl-2019-316105

[2] World Health Organization, 13 April 2021, https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases .

[3] S. Pal, M. Mitra," Empirical mode decomposition-based ECG enhancement and QRS detection", Comput. Biol. Med, vol 42 (2012), pages 83–92, ,http://dx.doi.org/10.1016/j.compbiomed.2011.10.012.

[4] E. Ercelebi, "Electrocardiogram signals denoising using lifting-based discrete wavelet transform", Comput. Biol. Med vol 34, September 2004, Pages 479-493, https://doi.org/10.1016/s0010-4825(03)00090-8 .

[5] R. Sameni, M. Shamsollahi, C. Jutten et al., "A nonlinear Bayesian filtering framework for ECG denoising", IEEE Trans. Biomed. Eng., vol 54, (2007), pages 2172–2185, http://dx.doi.org/10.1109/TBME.2007.897817 .

[6] M. Blanco, B. Weng, K. Barner, "ECG signal denoising and baseline wander correction based on the empirical mode decomposition", Comput.Biol. Med, vol.38, (2008), pages 1–13 https://doi.org/10.1016/j.compbiomed.2007.06.003.

[7] W. Jenkal, R. Latif, A. Toumanari, A. Dliou, O. El B'Charri, F.M.R. Maoulainine, "An efficient algorithm of ECG signal denoising using the adaptive dual threshold filter and the discrete wavelet transform", Biocybern. Biomed. Eng., vol 36, (2016), pages 499–508, http://dx.doi.org/10.1016/j.bbe.2016.04.001 .

[8] M. Rakshit, S. Das, "An efficient ECG denoising methodology using empirical mode decomposition and adaptive switching mean filter", Biomedical Signal Processing and Control, vol 40 ,(2018) ,pages 140–148, https://doi.org/10.1016/j.bspc.2017.09.020 .

[9] M. Hossain, S. Khairul Bashar, J. Lazaro et al., A Robust ECG Denoising Technique Using Variable Frequency Complex Demodulation, Computer Methods and Programs in Biomedicine, (2020), https://doi.org/10.1016/j.cmpb.2020.105856

[10] B. H. Tracey and E. L. Miller, "Nonlocal Means Denoising of ECG Signals," IEEE Trans. Biomed. Eng., vol. 59, no. 9, pp. 2383–2386, Sep. 2012, doi: 10.1109/TBME.2012.2208964

[11] L. Appeltant, M. Soriano, G. Van der Sande et al.," Information processing using a single dynamical node as complex system", Nature Communications, vol 2, (2011), pages 468–472, https://doi.org/10.1038/ncomms1476 .

[12] Zhong, Y., Tang, J., Li, X. et al. Dynamic memristor-based reservoir computing for high-efficiency temporal signal processing. Nat Commun 12, 408 (2021). https://doi.org/10.1038/s41467-020-20692-1

[13] M. cucchi C. Gruener et al.," Reservoir computing with biocompatible organic electrochemical networks for brain-inspired biosignal classification",
SCScience Advance, vol 7,(2021), https://doi.org/10.1126/sciadv.abh0693

[14] A.Jalalvand, K. Demuyncka, W. D. Neve, et al., on the application of reservoir computing networks for noisy image recognition, Neurocomputing 277(2018) 237-248 ,https://doi.org/10.1016 /j.neucom .2016.11.100 .

[15] K.Hamedani, L.Liu, R.Atat et al., Reservoir Computing Meets Smart Grids: Attack Detection Using Delayed Feedback Networks, IEEE Trans. on Industrial Informatics 14 (2018) 734 – 743, https://doi.org /10.1109 /TII .2017.2769106 .

[16] R. M. Nguimdo, G.Verschaffelt, J.Danckaert et al., Reducing the phase sensitivity of laser-based optical reservoir computing systems, Optics Express 24(2016) 1238-1252, https://doi.org/10.1364/OE.24.001238 .

[17] H. Jaeger,"Short term memory in echo state networks". Technical report, German National Research Center for Information Technology, 2001.

[18] P. Joshi and W. Maass, "Movement generation and control with generic neural microcircuits", In Proc. of BIO-AUDIT, pages 16–31, 2004.

[19] H. Burgsteiner," Training networks of biological realistic spiking neurons for real-time robot control", In Proc. of EANN, pages 129–136, Lille, France, 2005.

[20] H. Burgsteiner, "On learning with recurrent spiking neural networks and their applications to robot control with real-world devices", PhD thesis, Graz University of Technology, 2005.

[21] W. Maass, R. A. Legenstein, and H. Markram," A new approach towards vision suggested by biologically realistic neural microcircuit models", In Proc. of the 2nd Workshop on
Biologically Motivated Computer Vision, 2002.

[22] W. Maass, T. Natschl¨ager, and H. Markram," A model for real-time computation in generic neural microcircuits", In Proc. of NIPS, pages 229–236, 2003.

[23] D. Verstraeten, B. Schrauwen, D. Stroobandt, and J. Van Campenhout," Isolated word recognition with the liquid state machine: a case study". Information Processing Letters,
95(6):521–528, 2005

[24] M. D. Skowronski and J. G. Harris,"Minimum mean squared error time series classification using an echo state network prediction model", In Proc. of ISCAS, 2006.

[25] E. Morán ,C. Soriano , I. Fischer et al., Electrocardiogram Classification Using Reservoir Computing With Logistic Regression, IEEE.Biomed.19(2014) 892 – 898 , https://doi.org/ 10.1109/ JBHI. 2014. 2332001.

[26] A. Jalalvand,W. De Neve,Rik Van et al., Towards using Reservoir Computing Networks for noise-robust image recognition, IEEE, 2016, https://doi.org/10.1109/IJCNN.2016.7727398 .

[27] A. Jalalvand, K. Demuynck, J.Pierre, Feature enhancement with a Reservoir-based Denoising Auto Encoder,IEEE,2014, https://doi.org/10.1109/ISSPIT.2013.6781884 .

[28] G. Moody, R. Mark, The impact of the MIT-BIH arrhythmia database, IEEE Eng. Med. Biol. Mag., vol 20, (2001), pages 45–50, http://dx.doi.org/ 10.1109 /51 .93 2 724.

[29] J. Wang, Y. Ye, X. Pan, et al., Parallel-type fractional zero-phase filtering for ECG signal denoising, Biomed. Signal Process. Control, vol 18, (2015), pages 36–41, http://dx.doi.org/10.1016/j.bspc.2014.10.012 .

[30] W. Jenkal, R. Latif, A. Toumanari et al., "An efficient algorithm of ECG signal denoising using the adaptive dual threshold filter and the discrete wavelet transform", Biocybern. Biomed. Eng. vol 36, (2016), pages 499–508, http://dx.doi.org/10.1016/j.bbe.2016.04.001

Title Arabic:

تقليل الضوضاء في مخطط كهربية القلب باستخدام بنية حوسبة الخزان الديناميكي أحادية العقدة

Arabic Abstract:

يتطلب الكشف الدقيق لأمراض القلب إشارات نقية لمخطط كهربية القلب وهذه غير متوفرة في واقعنا. أثناء الاكتساب والإرسال، تتسبب أنواع الضجيج المختلفة في تلف إشارات مخطط القلب النقية مما يجعل من الصعب التشخيص. هنا، نقوم بتطبيق بنية حوسبة الخزان أحادية العقدة، استنادًا إلى الشبكات العصبية المتكررة لحل هذه المشكلة عن طريق تقليل ضجيج اشارة العضلات القياسية، وتداخل خط الطاقة الذي يفسد إشارات تخطيط القلب. نحصل على البيانات من قاعدة بيانات قياسية على الإنترنت لقياس عدم انتظام ضربات القلب. لتقييم بنية حوسبة الخزان أحادية العقدة، نستخدم مقياسين للأداء، وهما تحسين نسبة قدرة الإشارة إلى قدرة الضجيج والنسبة المئوية لمتوسط الجذر التربيعي. تتفوق بنية حوسبة الخزان أحادية العقدة المقترحة على أحدث التقنيات الحديثة ، مما يحقق نسبة تحسين قدرة الإشارة إلى قدرة الضجيج أعلى و النسبة المئوية لمتوسط الجذر التربيعي أقل لجميع أنواع الضوضاء الملوثة التي تم فحصها. تُظهر هذه النتائج مقدرة بنية حوسبة الخزان أحادية العقدة المقترحة على استعادة ديناميكيات إشارات تخطيط القلب في الجسم الحي بكفاءة.