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Noise-Removal from Spectrally-Similar Signals Using Reservoir Computing for MCG Monitoring

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***Abstract*—Continuous low-rate monitoring is an important IoT application, which requires high-fidelity in observing signals with low frequency. However, most sensors exhibit noise that is inversely-proportional to spectral frequency ($1/f$ noise). Because both the relevant signal and noise share the same spectral properties, standard linear filtering techniques cannot be used. We are looking into a special application for remote healthcare of the magnetic field sensing of cardiac activity, magnetocardiography (MCG). For such an application, we need to develop a noise separation method, that is also resource-efficient. Previously, we demonstrated AI-based removal of $1/f$ noise in MCG by a convolutional neural network coupled with gated recurrent units. However, it needs a large amount of data for training, requiring significant training time and computational power. In this work, we employ reservoir computing (RC) for noise-removal, while being conservative in computing resources.**

***Index Terms*—Smart health, Internet of Things (IoT), reservoir computing, noise, spintronic sensor, medical analytics.**

I. Introduction

Recently, with the massive adoption of the IoT (Internet of Things) sensors and wearable devices, there has been a significant push toward collecting and analyzing health data of patients, elderly citizens, athletes, and ordinary users with an aim to enhance the everyday quality of life of humans. Cardiac health is a crucial concern in both developed and developing countries, and numerous smartphone-based applications are now available to passively monitor the heartbeat and even electrocardiography (ECG). However, the ECG data sensing using these commodity devices are not accurate compared to clinical-grade ECG machines, which are intrusive in general due to the need to place electrodes or leads on the human body. During the ongoing pandemic of COVID-19 [1], the continuous remote monitoring of patients with cardiovascular conditions is needed to predict any complications, especially that care will be limited in an overwhelmed medical system.

Therefore, we need a cardiac sensing technology that is portable, non-intrusive, and compatible with IoT technologies. In this vein, an earlier work [2] demonstrated the acquisition of magnetocardiography (MCG) signals using spintronic magnetic tunnel junction (MTJ) sensors that operate at room temperature. Therefore, our spintronics-based monitoring of MCG is a high-impact solution for accurately monitoring the cardiac health of the masses. However, there are two interlinked challenges, and in Fig. 1 we propose to combine MTJ sensors [3] with AI-based signal and data analysis at the sensing node. The first challenge is that sending unprocessed data consumes a lot of communication bandwidth and power and constitutes a privacy risk. The second is the presence of noise, which requires cleaning before transmission. While MCG does not require contacting leads, it typically requires a magnetic-shielding to avoid environmental magnetic noise. Furthermore, the magnetic sensors themselves produce noise that is inversely proportional to spectral frequency ($1/f$ noise). The $1/f$ noise can be seen as correlated fluctuations at short time scales, which can obscure the similar dynamics of the cardiac activity [4]. Therefore, we need lightweight local AI solutions that can remove noise and monitor cardiac irregularities, such as arrhythmia, ischemia, and so forth. In this work, we are focusing on the more challenging task of noise-removal.

In our previous work [3], AI noise filtering based on a convolutional neural network (CNN) model with gated recurrent units (GRUs) reduced $1/f$ noise power by ten times compared to the moving average filtering. However, such a model required extensive training, and in unpredictable environments, it may require retraining in the cloud. This repeated process is both time-consuming and costly. The excellent performance and training challenge come from the recurrent part of the model. The recurrent neural networks (RNN) can process the temporal context of sensor information and deal with multi-

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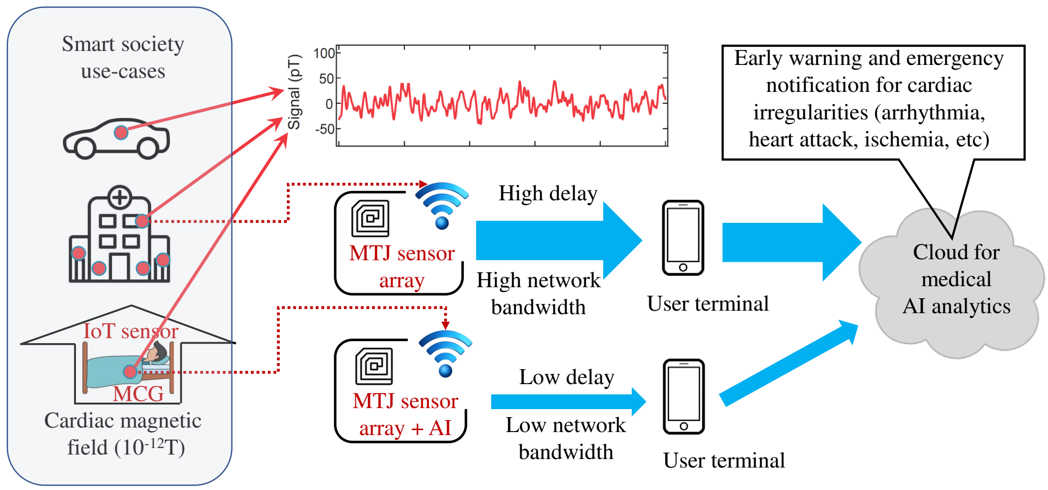

Fig. 1: Continuous MCG monitoring with conventional and proposed paradigms without and with AI model for smart and localized noise processing and medical analytics using spintronic devices.

ple information from different sources, but RNN training is expensive and complex [5]. Recently, a subset of RNNs has come to prominence, called "*Reservoir Computing*" (RC) [6]. The *reservoir* here refers to a large network of interconnected state variables that are non-linear to their excitation with fixed connection weights as depicted in Fig. 2, akin to the dynamics of waves in a water tank, magnetization dynamics, non-linear optics, *etc.*. RC has been investigated intensively in many spin, optical, memristor systems [7]. The rich dynamics of the RC map temporal data sequences into different trajectories in a high-dimensional space (hyperspace). Then, the training task is only limited to a readout layer to produce useful classifications or inferences from the reservoir's transient states. In this work, we show how to utilize RC to remove $1/f$ noise from the MCG signal. Using computer-based simulations, we demonstrate the RC method's effectiveness in terms of accuracy, memory requirement, and execution time.

The remainder of the paper is organized as follows. Section II presents preliminaries of spintronic sensors for embedding edge intelligence and also describes the fundamental problem considered in this work. Next, in section III, we provide a reservoir computing-based $1/f$ noise minimization of the envisioned smart IoT sensor. The performance of our proposed reservoir computing methodology is evaluated and compared with existing techniques in section IV. Finally, the paper is concluded in section V.

II. Preliminaries of Spintronic Sensors for Embedding Edge Intelligence and Problem Description

The MTJ sensors are made from two ferromagnetic metals (FMs) separated by an insulating tunneling barrier (e.g., magnesium oxide). The application of an external magnetic field (H) changes the magnetization angles of the FMs. Owing to the tunneling magnetoresistance effect (TMR), the resistance of MTJs depends linearly on H. Thus, MTJ sensors are simple to measure and can be combined with the integrated circuit fabrication process. MTJ sensors and structures are the main drivers of spintronics research and information storage applications, see Ref. [8] for a review. In the next generation networks, embedded edge intelligence is regarded as a crucial enabler for reducing bandwidth use, energy consumption, and end-to-end communication delay for network nodes [9]. Because embedding intelligence onto typically resource-constrained IoT nodes to facilitate edge computing is challenging [10], [11], the implementation of the theoretically appealing logic-in-sensor concept still remains illusive to implementation at a mass-scale.

The main challenge for sensors is the noise at the low-frequency side of the spectrum. The MTJ sensor's noise is dominated by a $1/f$ character, similar to many other systems [12]. According to [13], this issue worsens in the high sensitivity area. The power spectral density (PSD) of low-frequency noise can be represented as [14]:

$$S_v \propto \frac{\chi}{f^\beta}, \quad (1)$$

where χ is related to the sensor sensitivity, f is the spectral frequency, and β is the exponent of noise spectrum.

The cardiac dynamics are slowly-varying and stochastic. Therefore, the signal-of-interest and noise share the same $1/f$ character, which introduces a problem of separating two chaotic sources. The linear time-invariant filters, such as the moving average filtering, are traditionally used for noise-removal but cannot separate cardiac activity noise with considerable efficiency. The deep learning (DL) filtering in our earlier work [3] showed a 10-times decrease in noise power over the moving average technique. However, the retraining overhead could be a potential bottleneck for the practical deployment of deep learning models to the resource-constrained IoT devices for monitoring time-series signals such as MCG. Therefore, the challenge in this research is to model an alternative solution, which is practical as well as lightweight, to significantly reduce the training time to mitigate the $1/f$ noise and provide the corresponding ECG from the noisy MCG with high accuracy.

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We propose an RC technique based on Echo State Network (ESN) for predicting the ECG signal from the sensed MCG signal.

III. Envisioned Echo State Network (ESN) for Noise-Removal

As a proposed noise filtering technique, we have adopted the ESN-based RC, which is considered a subset of RNNs with randomly fixed connectivity weights [6]. The RC-based noise filtering and ECG estimating method consists of a reservoir part represented as sparsely connected units, and a readout part depicted as a regression paradigm. This ESN-based RC method is suited for temporal or sequential data processing at a low cost, making it a viable technique for noise filtering from the MCG signal to predict the corresponding ECG. The reservoir parts are fixed in the learning phase, and only the readout part is trained [15]. Hence, this fast learning method can result in lower requirements during the training/learning phase [16]. This characteristic of the RC-based noise filtering makes it feasible for hardware implementation utilizing physical systems such as the spintronic MTJ sensors.

The ESN-based RC method maps input MCG signals into higher dimensional space to achieve a deep non-linear representation of the input. A linear combination between the high dimensional space and the readout units is learned for efficient noise filtering inputs in a lightweight manner. The following eqs. 2, 3 depict the states of the reservoir nodes and the output nodes:

$$x_{t+1} = x_t(1-\alpha) + \Omega(W_i u_t + W_r x_t)\alpha \tag{2}$$

$$y_t = W_o \times x_t \tag{3}$$

Here, W_i represents the connection weights between the input and the reservoir units, W_r represents the weights of the recurrent connections within the reservoir, which are not trained, and the W_o indicates the readout weights which are trained during the learning/training phase. The discrete time-step values are taken to be, $(t = 1, 2, 3, \cdots)$. At the time t, the state of each reservoir is represented by x_t, the state of the output vector by y_t, and the input vector by u_t. The element-wise activation function is denoted as Ω, and α indicates the leaking rate. Here, the leaking rate (α) regulates the update frequency of the states.

Algorithm 1 depicts the workflow of selecting the best RC architecture in the training/learning phase and then utilizing the model to predict unknown data in the test/inference phase. The algorithm's input section demonstrates the details of each of the inputs provided to the algorithm. Instead of utilizing the whole MCG cycle as input to the RC model, smaller segments were used [3], each with a segment size of λ MCG samples. Therefore, the pre-processed dataset, denoted by X_{data}, contains a collection of λ MCG samples as input features, and a single, corresponding ECG sample is the output label.

The algorithm begins with initializing the expected parameters in steps 1 and 2. In step 3, the pre-defined splitting ratios (s_{train} and s_{test}) are employed to distribute the X_{data} for

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Algorithm 1: Proposed RC-based training algorithm for $1/f$ noise filtering at MTJ-based sensor for automated MCG-ECG mapping.

Input : X_{data} (pre-processed dataset containing multiple instances of the schema $\{\lambda$ MCG samples as input features : 1 corresponding ECG sample as output$\}$), U (the set of number of reservoir units), Ω (activation function), α (leaking rate)

Output: M_t (the parameters of the selected model)

1 $M_t \leftarrow \emptyset$
2 $\varepsilon_{min} \leftarrow \infty$
3 X_{train}, X_{test} ← prepare the training and test data, respectively, from X_{data} based on the split ratios (s_{train} and s_{test}, respectively)
4 **foreach** *index* i = *1 to* $|U|$ **do**
5 $\quad M_i$ ← load the RC model employing $U[i]$, Ω, α
6 $\quad$ train the model (M_i) for X_{train} employing Eqs. (2) and (3)
7 $\quad \varepsilon_i$ ← compute performance of model (M_i) utilizing X_{test}
8 $\quad$ **if** *(*$\varepsilon_i < \varepsilon_{min}$*)* **then**
9 $\qquad \varepsilon_{min} \leftarrow \varepsilon_i$
10 $\qquad M_t \leftarrow M_i$
11 $\quad$ **end**
12 **end**
13 save the model parameters of the selected model (M_t)
14 return M_t

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training and test phases. From steps 4 to 12, the algorithm identifies the best performing RC architecture by adopting a varying number of reservoir units (U). The i_{th} RC model is loaded and trained in step 5 and 6 using X_{train}. Afterward, the model's performance is evaluated in step 7, employing X_{test}. As an initial performance indicator, we have considered the prediction error in Root Mean Square Error (RMSE) [17], [18]. The i_{th} model's performance is checked with that of the previously evaluated models in steps 8 to 11 and updated accordingly. In step 13, the selected model (M_t) is saved. Finally, the selected model (M_t) is returned in step 14. With this trained model, the $1/f$ noise filtering for MCG-ECG mapping can be conducted at the MTJ sensor in an online manner.

IV. Performance Evaluation

In this section, we evaluate the performance of our reservoir computing proposal and compare it with the traditional moving average (MA) filtering technique and the deep learning (DL) method described in [3]. We have adopted three different performance indicators to evaluate the proposed system with the MA and DL techniques, which give us a strong understanding of the effectiveness of the proposed approach. Firstly, we demonstrate the noise-filtered signal result visually to ensure that the proposed method can resemble the original ECG signal. Then, we determine the Root Mean Squared Error (RMSE)

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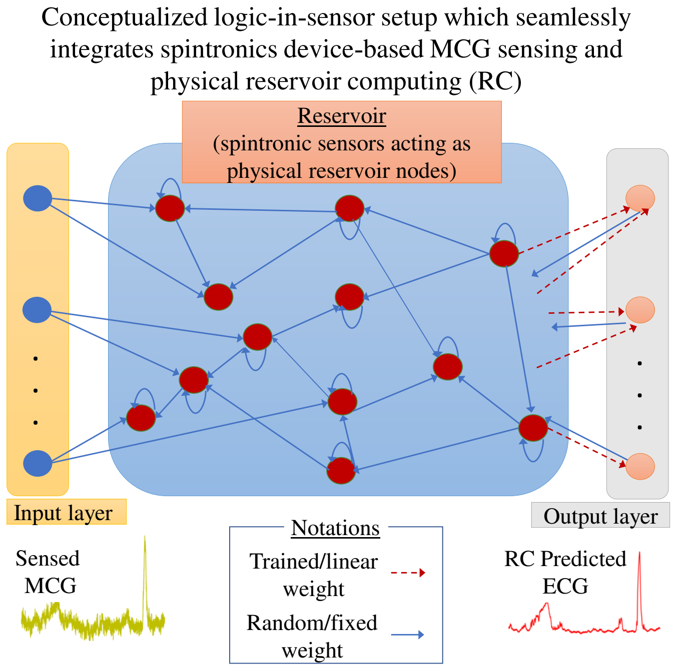

Fig. 2: Continuous MCG monitoring with conventional and proposed paradigms without and with AI model for smart and localized noise processing and medical analytics using spintronic devices.

to calculate the error in signal prediction by each technique. Lastly, we illustrate the filtering efficiency in the power spectral density of the remaining noise after prediction.

A. Data Preparation

For performance comparison, we used the same data preparation methods as our previous work [3]. We synthesized MCG cycles from ECG cycles available in the open PTB Diagnostic Database [19], [20], using the data preparation setup from our earlier work in [3]. We used the ECG traces from lead II of the healthy individuals. They were divided into single cardiac cycles, starting from the R peak to the next QRS complex, with the following sequence ($RSTPQRS$). The traces are upsampled to 3008 sample points without padded zeros, corresponding to a sampling frequency (f_s) of 2000 Hz. Then, the preconditioned ECG cycle is added to numerically-generated $1/f$ noise. We generated 100 MCG cycles with different noise sequences for each ECG cycle. We generated the $1/f$ noise from a white noise floor of PSD $= 10^{-18}V^2$/Hz, based on the characters from real measurements [2]. The knee frequency between $1/f$ and white noise is set at $f_k = 250$ Hz $= 0.125f_s$. After the data collection and pre-processing, the MCG and original ECG cycles are used to train the deep learning model depicted in Fig. 2.

B. Simulation Parameters

The simulations for experimental results were conducted using Python 3 libraries (e.g., NumPy, Pandas, Matplotlib, and Scikit-learn) for data processing and visualization purposes. The RC and DL-based models are primarily implemented employing TensorFlow with Keras library in python. For all the experimental simulations, we have equally split X_{data}, i.e., both s_{train} and s_{test} are set to 0.5. In terms of the proposed RC method, we have examined different architectures considering $U \in \{10, 30, 50, 70\}$. For each RC architecture, the hyperbolic tangent ($\tanh$) was used as the activation function (Ω). The value of the leaking rate (α) was fixed at 0.1. The weight values for W_i and W_r were initialized randomly. The number of input MCG samples per segment, λ, in both the RC and DL models was set to 50.

The RC-based proposal was compared with a DL-based (CNN and GRU) noise-filtering technique, the structure which was adopted from our previous work [3]. The epoch was set to 30 for the DL training phase. In terms of the moving average filtering technique, we have employed a striding length of 50 samples to filter the MCG to be consistent with the value of λ.

C. Results and Discussion

The simulations are conducted multiple times, and the average is used as the result. First, Fig. 3 demonstrates the filtering by the traditional moving average method, the deep learning method [3], and our proposed RC approach to jointly sense and minimize the $1/f$ noise in the input MCG signal. For ease of reference, we refer to the moving average filtering and deep learning method as MA and DL, respectively. Notice that the predicted ECG from the reservoir computing model is quite close to the original ECG/MCG cycle and successfully identifies the essential features such as the R-peak of the input ECG/MCG signal.

Next, Fig. 4 demonstrates the error in terms of the root mean squared error (RMSE) for the proposed reservoir computing-based model where the number of reservoir units is varied between 10, 30, 50, and 70. The errors incurred for these different configurations of the reservoir computing-based proposed method are compared with our earlier deep learning-based approach and the traditional moving average technique for noise processing. As shown in the result, when the number of reservoir units is set to 10, the error value is just above 0.07%. For increasing the number of reservoir units, the echo state network experiences more chaotic behavior in the state variables that slightly increases the error. Interestingly, the error remains much below 0.08% for the highest number of reservoir units considered (i.e., 70). On the other hand, the deep learning-based method results in the incurred error to reach 0.08%, whereas the moving average approach leads to the highest error.

Fig. 5 shows the filtering efficiency as seen in the power spectral density of the remaining noise after prediction, i.e., PSD (predicted-original). Notice that the spectral frequency is normalized by the sampling frequency, i.e., f/f_s. The RC and the deep learning predictions show a noteworthy reduction in noise power compared to the moving average filtering technique, especially at the crucial low-frequency region $f/f_s = 0.01$ – 0.03. Interestingly, the proposed reservoir computing-based method exhibits better performance for $f/f_s > 0.04$ as the

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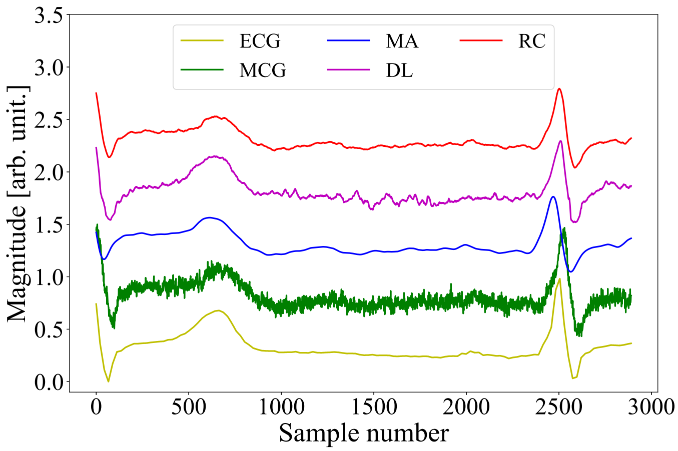

Fig. 3: Performance evaluation demonstrating the original ECG cycle, synthetic noisy MCG cycle used as input, comparison between conventional moving average method, DL-based method, and proposed RC-based (RC-10) approach to process and remove the input signal's noise. The curves are vertically shifted for clarity.

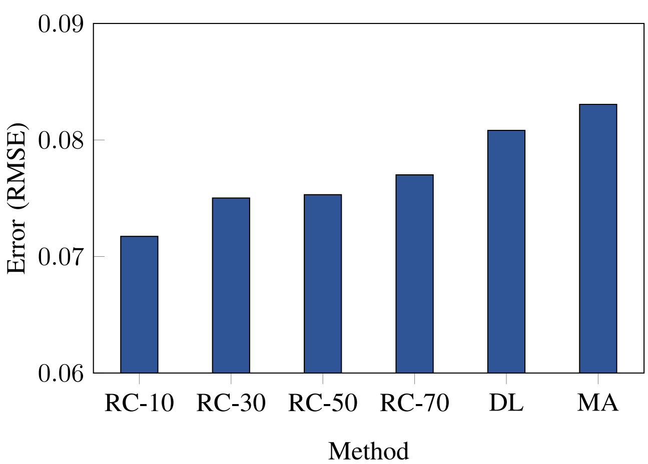

Fig. 4: Inference performance comparison of RC with moving average and deep learning methods.The different RC architectures consist of 10, 30, 50, and 70 units, respectively.

underlying ESN attenuates the high-frequency components that are not related to the QRS complex.

Next, whether the RC proposal is, indeed, lightweight is shown in Fig. 6 by taking into account the execution time and memory overhead of our reservoir computing-based method for the resource-constrained IoT device. Fig. 6(a) demonstrates the memory consumption rates during the training phase of the proposal for the various settings of the proposal where the number of reservoir units is varied from 10 to 70. The memory consumption for the lowest and highest numbers of reservoir units was found to be 0.45% and 0.89%, respectively. On the other hand, the memory required for the deep learning prediction-based method was 0.77%, which is significantly higher than the proposal with 10, 30, and 50 reservoir units.

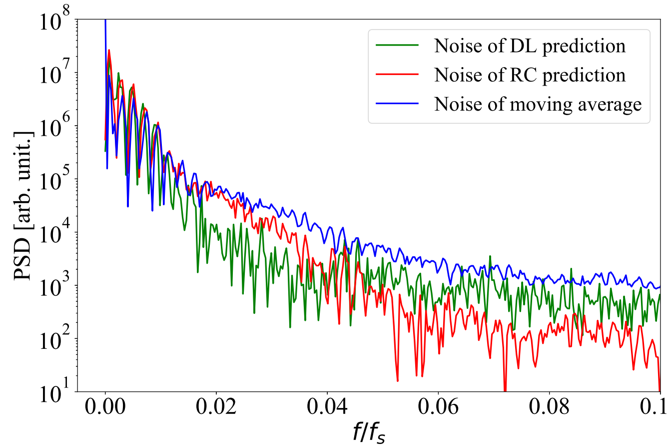

Fig. 5: Dependence of noise power on spectral frequency for the RC-based prediction method, DL-based prediction, and the moving average filtering. Spectral frequency is normalized.

On the other hand, Fig. 6(b) shows the average training and inference time requirements for the different configurations of our RC proposal and the deep learning prediction-based approach. Notice that while the average inference time for all the configurations is reasonably low (with increasing error rates, however, as earlier reported in Fig. 4). The average training time for all the configurations of our RC proposal is relatively constant and much faster than the deep learning method. Because RC training is limited to the output weights, the RC method has the advantage over the deep learning counterpart that requires retraining in the cloud, which incurs further network overheads and transmission delays. Thus, we may conclude that our proposal is a lightweight one suitable for IoT.

V. Conclusion

Recently developed spintronic devices have a vast potential for constructing smart and edge computing-capable IoT sensors with high sensitivity and low energy, particularly for magnetic biosignal detection (*e.g.*, MCG) at room temperature. However, their deployment is challenged by the $1/f$ noise, which is inherently present in such devices, interfering with the bio-signals of interest. This paper addressed this problem in the cardiac magnetic signal sensing use-case and proposed a reservoir computing model based on echo state networks. Through simulations, we demonstrated that the RC model is lightweight in terms of much lower training time and memory requirements. Therefore, it is promising for continuous health monitoring. The accuracy of the RC method is also found to be better than the conventional moving average filtering and comparable with a recent DL approach. The simulation-based results are encouraging and can be regarded as a proof-of-concept basis for the physical reservoir computing implementation, using the sensors as physical RC model units to jointly sense and analyze the sensed bio-signals at the "ultra-edge" of the IoT ecosystem.

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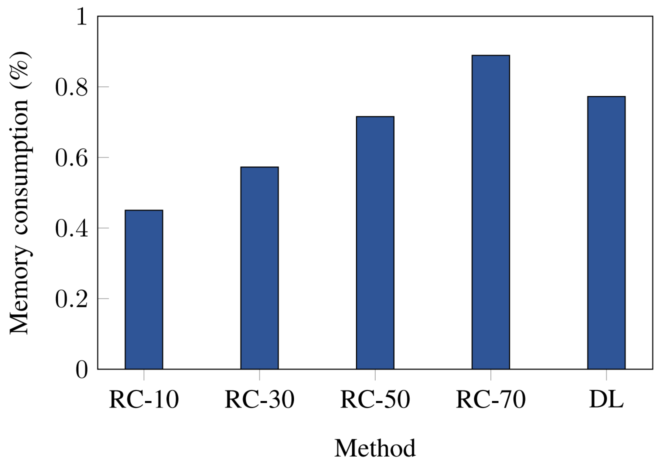
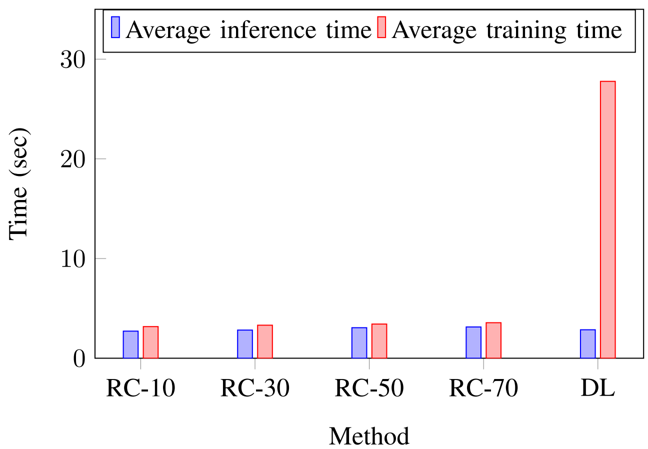


(a) Memory consumption rate in the training phase for different settings of RC and DL methods.



(b) Required time (per cycle) in the training and inference phases for different settings of RC and DL methods.

Fig. 6: Memory and time requirement for the RC architectures and DL method. The different RC architectures consist of 10, 30, 50, and 70 units, respectively.

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