This is the author's version of an article that has been published in IEEE.
The final version of record is available at https://doi.org/10.1109/IoTaIS53735.2021.9628824

A Circuit-embedded Reservoir Computer for Smart Noise Reduction of MCG Signals

Biraj Shakya*[1], Mostafa M. Fouda*[2], Steve C. Chiu*[3], and Zubair Md Fadlullah†‡[4].
*Department of Electrical and Computer Engineering, Idaho State University, Pocatello, ID, USA.
†Department of Computer Science, Lakehead University, Thunder Bay, Ontario, Canada.
‡Thunder Bay Regional Health Research Institute (TBRHRI), Thunder Bay, Ontario, Canada.
Emails: [1]birajshakya@isu.edu, [2]mfouda@ieee.org, [3]stevechiu@isu.edu, [4]zubair.fadlullah@lakeheadu.ca.

***Abstract*—With the COVID-19 pandemic, it has become necessary to monitor cardiac activities, not only for heart patients but for everyone. However, the traditional way to use heavy machines which are non-portable, intrusive, to check the electrocardiography (ECG) is not possible for everyone. As an alternative, there are sensors that can collect magnetocardiography (MCG) signals by measuring the magnetic field produced by the electrical currents in the heart and can be converted into ECG signals. The sensor for MCG is very sensitive, consume low power, portable, and can be a good alternative to check cardiac activities. But the challenging part of these sensors would be the noise at the low frequencies because the heart also oscillates at the low frequencies. As the relevant signal and noise share the same spectral properties, standard linear filtering techniques are not efficient. In this paper, we propose a physical reservoir computing technique using a circuit that can act as a reservoir and a lightweight machine learning model. The output is modeled to reduce the noise and extract the ECG signals out of the MCG ones.**

***Index Terms*—Reservoir computing, smart health, Internet of things (IoT), noise, medical analytic, ECG, MCG.**

I. Introduction

Living in a world powered by the Internet of Things (IoT), we can do almost everything with a push of a button, or in some cases, it just does automatically. As an example, the smartwatches can track how many steps you have walked and sometimes the smartwatches can also monitor the stress levels. There are so many great advancements in technologies in various fields. However, with all the developments in all the sectors, there is still a lot of research that needs to be done to find the best way to monitor the human heart signals rather than going to hospitals and using the traditional electrocardiogram (ECG) machines. With the ongoing COVID-19 (coronavirus disease of 2019) [1]–[3] and its variants, regular check-up on cardiac activity has become more important than ever and going to hospitals is not an option for everyone. Nobody knows how many COVID-19 variants will be there so we need to be prepared. Not just because of the COVID-19, according to [4], cardiovascular diseases are considered as the leading cause of death worldwide, which results in approximately 31% of all global deaths; however, the risk can be eliminated/mitigated if it is detected and diagnosed with a timely treatment.

There are some applications on the smart phones and also some devices which can be connected with the smart phones to measure the ECG signals, however, these are not accurate compared to the clinical-grade ECG machines in the hospitals. So, as an alternative to measuring the ECG signals, there are sensors that can measure the magnetocardiography (MCG) signals by measuring the magnetic fields produced by the electrical currents generated by the heart. This was demonstrated by an earlier work done by Fujiwara *et al.* [5] using a spintronic magnetic tunnel junction (MTJ) sensor. The sensors like MTJ are portable, consume low power, and can be used while doing daily activities. However, it does have a major challenge which is the noise at low frequencies. As the heart also oscillates at low frequency, filtering out the noise and monitoring cardiac irregularities is a major challenge of using the MCG sensors. To tackle this challenge, in this paper, we propose a circuit that can act as a reservoir for reservoir computing (RC) and with machine learning models, the output of the circuit can be modeled to reduce the noise of the MCG signal and convert it to an ECG signal which can be used later on to detect cardiac diseases such as arrhythmia [6]–[10].

The remainder of this paper is organized as follows. Section II presents the related work. Section III presents the problem formulation. Section IV shows how a chaotic circuit can be a reservoir for reservoir computing. Section V presents the proposed method to tackle the challenges. Section VI presents the performance evaluation of the proposed method. Section VII concludes the paper.

II. Related Work

The challenging part of using an MCG sensor such as MTJ is how to remove the low-frequency noise. In this vein, an earlier research work done by Mohsen *et al.* [11] used AI-based noise filtering which consists of a convolutional neural network (CNN) along with gated recurrent units (GRU) to reduce the noise. This method uses a recurrent neural network (RNN) where the recurrent process gives an excellent performance and reduces the noise of the signal by ten times compared to the moving average filter [11]. However, these deep learning modules need extensive training time.

On the other hand, a continuation to the work done by Mohsen *et al.*, a research done by Sakib *et al.* [12] used a Reservoir Computing (RC) technique based on Echo State Network (ESN) to reduce the noise of the MCG signals. The paper demonstrated computer-based simulations with the effectiveness of its methods. It shows a promising solution to the problem with a faster training time compared to the deep learning method but the inference time of the process is similar to the deep learning method done by Mohsen *et al.*, which can be a negative factor in order to use it in real-time scenarios.

This is the author's version of an article that has been published in IEEE.
The final version of record is available at https://doi.org/10.1109/IoTaIS53735.2021.9628824

III. Problem Formulation

The ECG is the electrical signal generated by the heart which shows the heart rate and rhythm. This signal can often be used to detect any heart diseases, abnormal heart rhythms that may cause heart failure [7]. With the increasing cases of COVID-19 and its new variants, checking up on ECG is becoming essential. However, to get the clinical-grade ECG signal, one has to go to the hospital which is not an option for a large number of people. As an alternative to the traditional way, a new technique that measures the magnetic field produced by the electrical activity of the heart known as MCG has come into the highlight. The sensor that measures an MCG signal can be a portable, low energy consuming device that can be fused on-chip with other logic circuits and connect to the IoT devices as well.

The MTJ sensor is one of the sensors that can efficiently measure the MCG. MTJ is a tri-layer sandwich that consists of two layers of ferromagnetic metals separated by an ultra-thin insulating film (0.7–1.6 nanometers). Due to the ultra-thin insulating layer, an electron can tunnel from one ferromagnet into the other creating a magnetoresistive effect known as tunnel magneto-resistance. It is an ultra-sensitive sensor that is capable of sensing the human heart as well as brain signals [5]. Due to its high sensitivity, it also senses noises that come from the heart itself. As the noise and the target signal oscillates in the same low-frequency band, removing the noise becomes another challenge for using these MTJ sensors. The linear time-invariant filter which is traditionally used for removing noise for a signal like MCG cannot separate cardiac activity noise with considerable efficiency. The deep learning method by Mohsen *et al.* [11] and the RC-based ESN method by Sakib *et al.* [12], both showed a considerable decrease in the noise, however, the training and testing time on both of the methods is high which is a drawback for practical deployment. Therefore, as a solution to these problems, in this paper, we investigate how a circuit which acts as a reservoir and a simple machine learning module can effectively reduce the noise with minimal time to train and test.

IV. Circuit as a Reservoir

A. Reservoir Computing

Reservoir Computing (RC) is considered to be the new and promising technique derived from Recurrent Neural Network (RNN) to be used for a time-series prediction. It was introduced by Lukosevicius and Jaeger *et al* in [13] and has attracted many researchers. As shown in Fig. 1, the RC mainly consists of three parts: the input, the reservoir, and the readout layer (output from the reservoir). The readout layer is the only layer that needs to be trained whereas both the input and the reservoir layers weights are randomly fixed. This is the main difference between an RC and an RNN as in RNN every layer needs to be trained which takes a lot of time.

In RC, the inputs are fed into the reservoir, where it is mapped into its higher-dimensional space. Then the state of the reservoir is mapped into the desired output using a simple machine learning model such as ridge regression. The

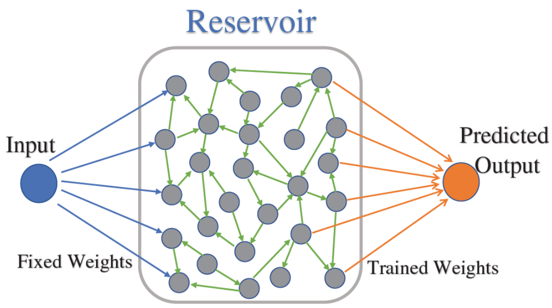


Fig. 1: Reservoir computing architecture.

reservoir can be anything. It can be any kind of a dynamical system such as a silicon photonic chip [14], a neuromorphic atomic switch networks [15], or even a bucket of water [16]. As long as it can be perturbed by the input and its output can be observed, anything can be a reservoir. So keeping that in mind, in this paper, we use a chaotic circuit as a reservoir.

B. Chaotic Circuit as a Reservoir

The circuit that exhibits chaotic behavior is a chaotic circuit. The chaotic behavior must be a non-periodic oscillator or an oscillating waveform that never repeats. The chaotic behavior makes a chaotic circuit dynamically rich and a unique set of time-varying output that never repeats makes a chaotic circuit a good choice for a reservoir.

There are many chaotic circuits that can be used as a reservoir. The one that we have chosen for this research is known as the Lindberg–Murali–Tamasevicius circuit (LMT circuit) which is introduced by Lindberg *et al.* [17]. The LMT circuit is one of the simplest non-autonomous circuits with a single transistor. The circuit is called a non-autonomous circuit as it contains a voltage source that produces a sine wave (a time-varying input) as shown in Fig. 2. The circuit consists of a sinusoidal source, two capacitors, two resistors, and a transistor (2N2222A), which makes it one of the simplest non-autonomous circuits.

Chaos sets in when the circuit drifts out of synchronization, i.e., if two circuits are coupled which are not in harmony. Chua circuit [18] is one of the examples of that type of chaos whereas this non-autonomous LMT circuit solely reports on the disturbance of the charging and discharging of the capacitor.

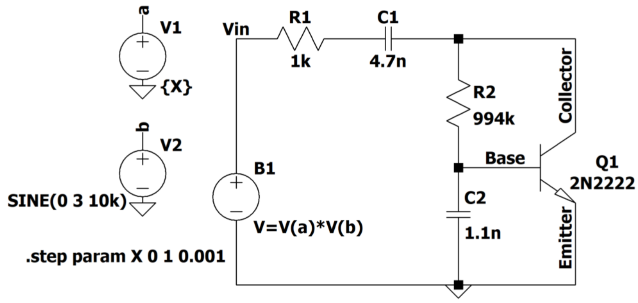


Fig. 2: LMT circuit.

This is the author's version of an article that has been published in IEEE.
The final version of record is available at https://doi.org/10.1109/IoTaIS53735.2021.9628824

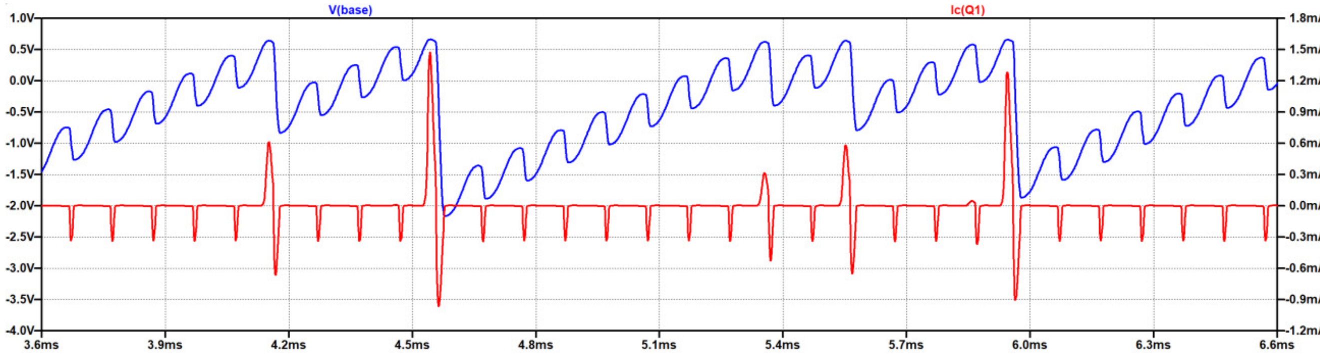


Fig. 3: The base voltage and the current flowing through the transistor vs. time.

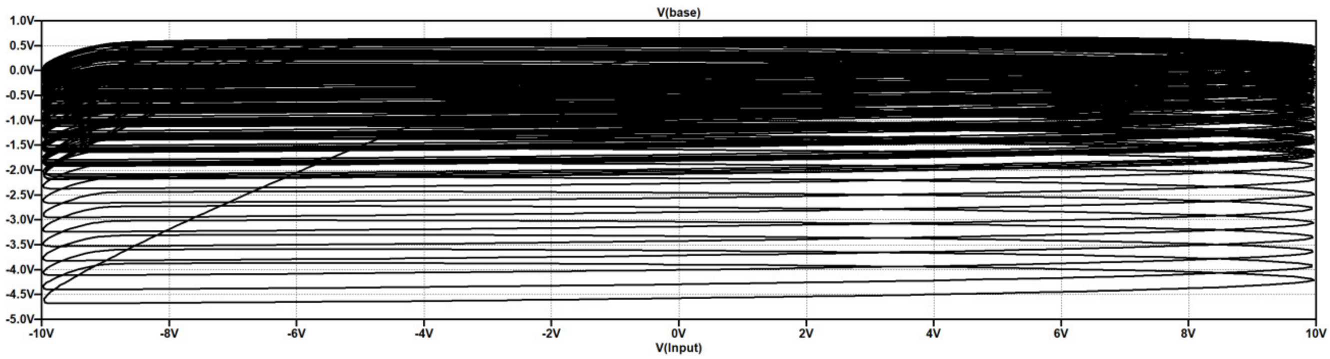


Fig. 4: Output of the circuit showing the chaotic behavior.

C. How does the circuit work?

The transistors can be forward-biased as well as reverse-biased depending on the base-emitter voltage. So, when the base-emitter voltage reaches about $0.65V$, the transistor turns on (forward-biased), which makes the current flow through the transistor.

From Fig. 3, we can see when the base voltage (in blue color) reaches about $0.65V$ there is a large positive spike of current flow (in red color) and this is followed by a large negative spike which is due to the discharging of the capacitor (or reverse-biased of the transistor). As the capacitor discharges, the voltage at the base goes down again and as the capacitor charges and discharges, the voltage will sometimes reach the $0.65V$ mark and then does the same thing. Hence, in short, the forward and the reverse-biasing of the transistor fights to charge the capacitor which makes this circuit chaotic.

The chaos is between the base voltage and the input voltage and can be seen in Fig. 4 using simulation tools.

V. Proposed Method

The LMT circuit is one of the simplest non-autonomous chaotic circuits. It consists of only few components which makes its implementation an easy task. In reality, the circuit has a variable sinusoidal voltage source but for the simulation purposes, it has a total of three voltage sources, a variable DC (direct current) source, a sinusoidal source, and another source that will multiply the first two sources. For simplicity, the maximum and the minimum values of the DC source are 1V and 0V, respectively, and the sinusoidal voltage source has an amplitude of 3V with 10 kHz frequency. As we change the DC source, the amplitude of the input changes accordingly giving out a unique output for every value of the DC source that does not repeat. The output of the circuit is the voltage at the base of the transistor which is a time-series data recorded at the same interval of time for every input. It is very important to make sure every point is recorded at the same interval of time since the circuit starts running, otherwise, the data would not be comparable. The LMT circuit contains 2 capacitors and they could be charged from the previous runs so the circuit should be reset for every run as well.

The main input for the circuit is the variable DC source and this source corresponds to the detected MCG signal. But the MCG signals are in the range of 10^{-6} so it needs to be normalized in the range of the DC source, i.e., from 0 to 1. This can be done by the following simple normalization formula:

$$z = \frac{x - min}{max - min}, \tag{1}$$

where z is the normalized MCG, x is the detected MCG, and max and min are the maximum and minimum of the whole set of detected MCG values.

After normalization, the MCG values would be the main input to the circuit. Then for every value, the circuit will run for a certain time, recording points at fixed intervals for all the inputs and resetting after every input. In the end, every normalized MCG value will have a set of unique time-series data which are called features. A similar process was done by Jensen *et al.* [19] in which a chua circuit [18] was used as a reservoir to predict the 7^{th}-degree polynomial on a certain range.

The training and testing data are generated separately. Then by training a simple machine learning model, the features are mapped into their corresponding ECG values. The simple machine learning model we used in this paper is known as ridge regression or L2 regularization. The reason we selected this model is because it reduces the overfitting problem while predicting and is widely adopted within the RC community. The Ridge Regression loss function is given by:

$$L = \sum (y - \hat{y})^2 + \alpha \sum m^2, \quad (2)$$

where $\sum (y - \hat{y})^2$ is the sum of squared residuals (SSR), y is the true value, $\hat{y}$ is the predicted value, $\alpha \sum m^2$ is the penalty term, α is the control parameter, and m is a coefficient.

The control parameter α must be chosen carefully because its optimal value will change with a slight variance in the data whereas the coefficient 'm' shows how much a feature contributes to predicting the actual output. The ridge regression simply aims to minimize the loss function as much as possible with the given parameters.

Subsequently, the prediction score and the root mean square error (RMSE) are calculated which show the model's performance in predicting the true values. The general idea of the whole method is shown in Fig. 5.

VI. Performance Evaluation

In this section, we evaluate the performance of our proposed circuit reservoir and compare it with the moving average (MA) method. We have two major performance indicators, the prediction score which is also known as the R2 score, and the root mean square error (RMSE). These two will give us a strong understanding of the effectiveness of the proposed approach.

A. Data Preparation

For simplicity, we pre-run the circuit with input from 0 to 1 with 1000 steps, resetting on every input. Then we compare it with the normalized MCG signal and get the features for all the MCG values which will save time and computational cost. Here, to compare, the normalized MCG signals are rounded up to 3 decimal places according to the input of the circuit.

The simulation software used to simulate the LMT circuit has a small limitation. While recording the output data, we could only specify a maximum time step instead of a minimum time step which means that the software automatically chooses the time step as long as it's below the specified maximum time step. Because of this flaw, the software will record the high number of data points where the output is changing and fewer data points where the output is stable. But for our research work, we need to record points at same time for every input. To overcome this problem, we had to specify a very small value for the maximum step size so that every time the circuit runs, the data points are recorded at the same time.

Doing this will create a huge number of data points. For the maximum time step size that we choose, a single input will have about 500000 data points and these data points are the features of the input which are the MCG values. This amount of data points are a lot for a single input so we select the number of features according to our needs. For example, if we want 1000 features, then we select every 500^{th} point and similarly, if we want 500 features, then we select every 1000^{th} point.

For performance comparison, we used the same data preparation methods as our previous work [11] and [12]. The MCG and ECG cycles were synthesized from the available open PTB Diagnostic Database [20], [21]. The ECG data are up-sampled to 1020 points without the padded zeros, corresponding to a sampling frequency of 2000 Hz. Then the ECG cycle is added to randomly numerically generated $1/f$ noise to generate MCG cycles. We generated 10 MCG cycles with different noises for each of the ECG cycles.

As in our previous work [11] and [12], the MCG signal is split into smaller segments, each with sample size n. The sample size we have chosen is 20 and the size of the features to be 101 which makes 2020 features (20*101) for each ECG data point.

We generated 50 sets of ECG cycles and their corresponding 10 MCG cycles with a total of 500 MCG cycles for training the model. With the sample size and the features, the final training data size is 500000 rows by 2020 columns.

B. Results and Discussion

The simulations are conducted multiple times, and the average is used as the result of this research work. Likewise, whenever possible, we have compared our research work with previous works. For training and testing the proposed model, we used ridge regression analysis. Fig. 6 demonstrates the filtering of the $1/f$ noise in the MCG signal by the traditional moving average (MA) method and our proposed RC circuit approach. We can notice that the predicted ECG from the RC circuit model is very close to the original ECG cycle and successfully identifies the essential features of the ECG signals.

For testing the model, we generated 50 separate sets of ECG cycles with their corresponding MCG cycles and the same rest of the process. Then the average of the 50 tests is shown as the results. Fig. 7(a) shows the average RMSE error for the proposed RC circuit model and the MA method. As shown, the RC circuit model has considerably less RMSE error (about 0.03) than the traditional moving average (MA) method (more than 0.06).

Another strong performance indicator for both models is the prediction score (also known as the R2 score). This score is calculated using the following formula.

$$R = 1 - \frac{\sum (true\ value - predicted\ value)^2}{\sum (true\ value - \overline{true\ value})^2}. \quad (3)$$

Fig. 7(b) shows the average prediction score of both methods for 50 sets of test data set. Note that the RC circuit's average prediction score is significantly higher than the MA method which shows the RC circuit method is good at predicting the output without overfitting the data.

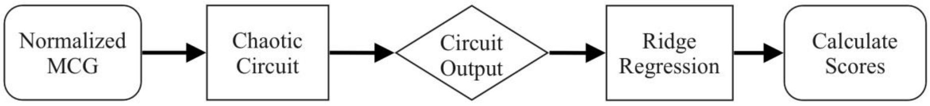


Fig. 5: Flow diagram of the proposed method.

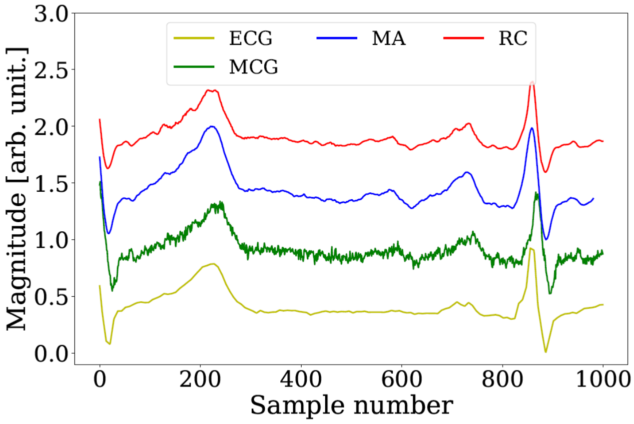
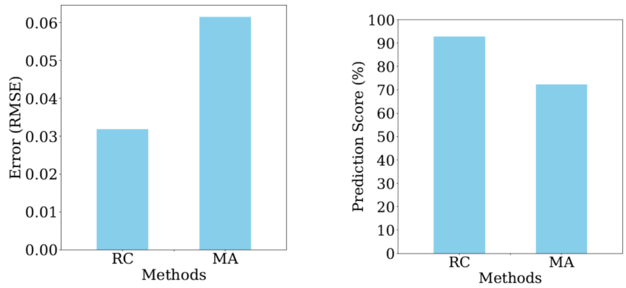


Fig. 6: Performance evaluation demonstrating the original ECG cycle, synthetic noisy MCG cycle used as input, comparison between traditional MA method and proposed RC circuit method. The curves are vertically shifted for clarity.



(a) Comparison of RMSE scores.

(b) Comparison of prediction scores.

Fig. 7: Performance evaluation of the RC circuit and MA methods.

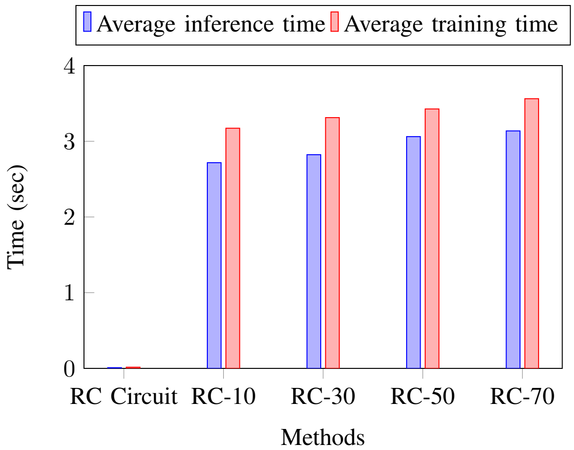


Fig. 8: Average inference and training time (per cycle) for RC circuit, ESN-based RC with 10, 30, 50 and 70 reservoir units.

As a result, the RC circuit method has lower RMSE score and higher prediction score and on top of that, it has very little training and inference time which is due the use of ridge regression analysis. The training part is done with the whole set of training data. The whole set which is 500 sets of MCG cycles with 2020 features, takes 7.73 seconds to train. Then training time per cycle would be $7.37/500$ and is equal to 0.0155 seconds on average. Similarly, the average test/inference time to predict the output from the features for an MCG cycle is 0.008652 seconds. This can be seen in Fig. 8 which is significantly less compared to the other methods, specifically, the ESN-based RC with 10, 30, 50, and 70 reservoir units [12] while the deep learning [11] method takes more than 20 seconds to train per cycle (not shown in the figure for clarity).

The residual plot is also considered to be an important plot for validating how well the model is predicting the output. There is no regression model that can give 100% accurate prediction to our problem. There is always some randomness and unpredictability in every regression model and this can be explained as:

$$Prediction = Deterministic + Stochastic. \quad (4)$$

The regression model tries to capture the deterministic part, however, the stochastic part of the data is completely random. Hence, the residuals should follow a normal distribution to be a good regression model [22].

The residual plot is simply a scatter plot between residuals (true output - predicted output) and predicted output. An example of a good residual plot with the normal distribution is shown in Fig. 9. Whereas Fig. 10 shows one of the residual plots from the testing part of our ridge regression model. Comparing with the good residual plot, the distribution is densely populated near the origin of the y-axis but it also has a little skewed distribution. This means that the ridge regression is capturing most of the deterministic part of the data but there is still some that need to be captured and with more training data it might give better performance.

Hence, we showed 4 performance indicators (prediction score, RMSE score, average time taken, and residual plot) of the model and each indicator showed that the proposed model is accurate, fast, and suitable for our implementation in ECG monitoring devices based on MCG signals.

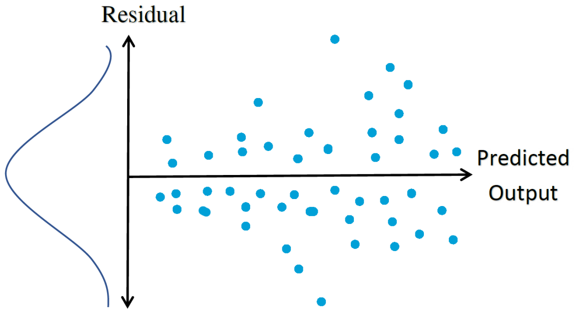


Fig. 9: Example of a good residual plot.

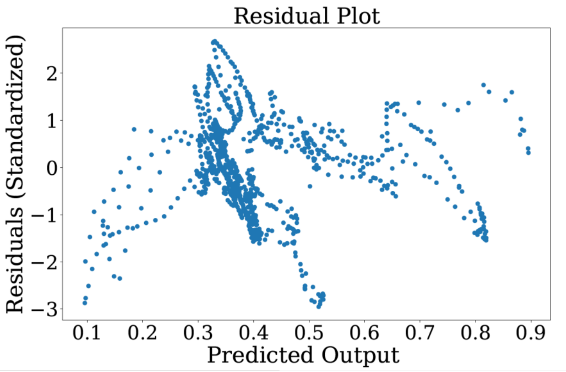


Fig. 10: Residual plot from the testing part.

VII. Conclusion

The highly sensitive sensors like MTJ have tremendous potential but are challenged by the low-frequency noises which interfere with the target signal. In this paper, we addressed this problem and proposed a reservoir computing (RC) circuit that can tackle this challenge. Through the simulations, we demonstrated that the RC circuit model is significantly accurate with much lower training and inference times. The accuracy of the RC circuit method is comparable with other methods like moving average, deep learning, or ESN-based RC methods, whereas the training and inference time is significantly reduced. The simulation-based results are encouraging and can be a proof of concept for the physical reservoir computing implementation. The chaotic circuit used in this paper is a simple one and can be implemented easily.

Acknowledgement

This research work was made possible by grant number NPRP13S-0205-200270 from the Qatar National Research Fund, QNRF (a member of the Qatar Foundation, QF). The statements made herein are the sole responsibility of the authors.

References

[1] Z. Fadlullah, M. M. Fouda, A. S. K. Pathan, N. Nasser, A. Benslimane, and Y. D. Lin, "Smart IoT solutions for combating the COVID-19 pandemic," *IEEE Internet of Things Magazine*, vol. 3, no. 3, pp. 10–11, Sep. 2020.

[2] S. Sakib, T. Tazrin, M. M. Fouda, Z. M. Fadlullah, and M. Guizani, "DL-CRC: Deep learning-based chest radiograph classification for COVID-19 detection: A novel approach," *IEEE Access*, vol. 8, pp. 171 575–171 589, Sep. 2020.

[3] S. Sakib, M. M. Fouda, Z. Md Fadlullah, and N. Nasser, "On COVID-19 prediction using asynchronous federated learning-based agile radiograph screening booths," in *ICC 2021 - IEEE International Conference on Communications*, 2021, pp. 1–6.

[4] S. Berrouiguet, M. L. Barrigón, J. L. Castroman, P. Courtet, A. Artés-Rodríguez, and E. Baca-García, "Combining mobile-health (mHealth) and artificial intelligence (AI) methods to avoid suicide attempts: the smartcrises study protocol," *BMC psychiatry*, vol. 19, no. 1, pp. 1–9, 2019.

[5] K. Fujiwara, M. Oogane, A. Kanno, M. Imada, J. Jono, T. Terauchi, T. Okuno, Y. Aritomi, M. Morikawa, M. Tsuchida, N. Nakasato, and Y. Ando, "Magnetocardiography and magnetoencephalography measurements at room temperature using tunnel magneto-resistance sensors," *Applied Physics Express*, vol. 11, no. 2, p. 023001, jan 2018.

[6] S. Sakib, M. M. Fouda, Z. M. Fadlullah, and N. Nasser, "Migrating intelligence from cloud to ultra-edge smart IoT sensor based on deep learning: An arrhythmia monitoring use-case," in *2020 International Wireless Communications and Mobile Computing (IWCMC)*, 2020, pp. 595–600.

[7] S. Sakib, M. M. Fouda, Z. M. Fadlullah, N. Nasser, and W. Alasmary, "A proof-of-concept of ultra-edge smart IoT sensor: A continuous and lightweight arrhythmia monitoring approach," *IEEE Access*, vol. 9, pp. 26 093–26 106, 2021.

[8] S. Sakib, M. M. Fouda, and Z. M. Fadlullah, "A rigorous analysis of biomedical edge computing: An arrhythmia classification use-case leveraging deep learning," in *2020 IEEE International Conference on Internet of Things and Intelligence System (IoTaIS)*, 2021.

[9] S. Sakib, M. M. Fouda, Z. M. Fadlullah, K. Abualsaud, E. Yaacoub, and M. Guizani, "Asynchronous federated learning-based ECG analysis for arrhythmia detection," in *2021 IEEE International Mediterranean Conference on Communications and Networking (MeditCom)*, 2021.

[10] S. Sakib, M. M. Fouda, and Z. M. Fadlullah, "Harnessing artificial intelligence for secure ECG analytics at the edge for cardiac arrhythmia classification," *Secure Edge Computing: Applications, Techniques and Challenges*, pp. 137–153, 2021.

[11] A. Mohsen, M. Al-Mahdawi, M. M. Fouda, M. Oogane, Y. Ando, and Z. M. Fadlullah, "AI aided noise processing of spintronic based IoT sensor for magnetocardiography application," in *2020 IEEE International Conference on Communications (ICC)*, 2020.

[12] S. Sakib, M. M. Fouda, M. Al-Mahdawi, A. Mohsen, M. Oogane, Y. Ando, and Z. M. Fadlullah, "Noise-removal from spectrally-similar signals using reservoir computing for MCG monitoring," in *2021 IEEE International Conference on Communications (ICC)*, 2021.

[13] M. Lukoševičius and H. Jaeger, "Reservoir computing approaches to recurrent neural network training," *Computer Science Review*, vol. 3, no. 3, pp. 127–149, 2009.

[14] K. Vandoorne *et al.*, "Experimental demonstration of reservoir computing on a silicon photonics chip," *Nature communications*, vol. 5, no. 1, pp. 1–6, 2014.

[15] H. O. Sillin, R. Aguilera, H.-H. Shieh, A. V. Avizienis, M. Aono, A. Z. Stieg, and J. K. Gimzewski, "A theoretical and experimental study of neuromorphic atomic switch networks for reservoir computing," *Nanotechnology*, vol. 24, no. 38, p. 384004, 2013.

[16] C. Fernando and S. Sojakka, "Pattern recognition in a bucket," in *European conference on artificial life*. Springer, 2003, pp. 588–597.

[17] E. Lindberg, K. Murali, and A. Tamasevicius, "The smallest transistor-based nonautonomous chaotic circuit," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 52, no. 10, pp. 661–664, 2005.

[18] L. O. Chua, "Chua's circuit 10 years later," *International Journal of Circuit Theory and Applications*, vol. 22, no. 4, pp. 279–305, 1994.

[19] J. Jensen and G. Tufte, "Reservoir computing with a chaotic circuit," in *Proceedings of the European Conference on Artificial Life 2017*. MIT Press, 2017.

[20] A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals," *circulation*, vol. 101, no. 23, pp. e215–e220, 2000.

[21] M. Kachuee, S. Fazeli, and M. Sarrafzadeh, "ECG heartbeat classification: A deep transferable representation," in *2018 IEEE International Conference on Healthcare Informatics (ICHI)*, 2018.

[22] U. Gohar, "How to use residual plots for regression model validation?" Mar. 2020, last Accessed: Aug. 27, 2021. [Online]. Available: https://towardsdatascience.com/how-to-use-residual-plots-for-regression-model-validation-c3c70e8ab378