Employing the Empirical Mode Decomposition to Denoise the Random Telegraph Noise

A. Moshrefi, H. Aghababa*, O. Shoaei

School of Electrical and Computer Engineering, University of Tehran, Tehran, Iran

1. INTRODUCTION

In recent years, the noise issue has attracted the attention of semiconductor industry. This phenomenon can decrease the quality of the valuable data and negatively impact the results of analysis and modeling. There are some methods to improve the quality of measuring the noise and data. However, if the noise and data are combined together, their discrimination will be tough. In addition, we have some limitations for our instruments which cannot accurately capture the desired data. Meanwhile, providing a solution by the software analysis would be helpful to obtain the data accurately [1–3].

In the other side, as the scaling of transistor geometries towards only a few tens of nanometers continues, we find that small devices face new challenges regarding their operation reliability. Random Telegraph Noise (RTN) is one of these challenges which happens by trapping and detrapping of the carriers in the transistor channel and it would make some variations on the drain current. RTN is one of the most important time variation sources having a prominent effect on the reliability of memories, digital and analog circuits [4, 5]. Therefore, capturing the features of RTN and its modeling is of great importance. If we can measure the RTN accurately, we can obtain an appropriate model for it. However, this measurement is usually affected by some noise and error and it calls for a method to improve the signal to noise ratio.

In this area, Karatsori et al. [6] have characterized and measured the low frequency noise in InAs MOSFET. Stampfer et al. [7] has characterized the noise produced by individual defects for MoS2 field-effect transistors. Waldl et al. [8] employed an advanced algorithm based on cumulative summation to detect the step levels in RTN. Jech et al. [9], Lai et al [10] and Ullmann et al. [11] have extracted and measured the low frequency noises in MOSFET and also they have introduced a model for the noise features. Feng et al. [12] investigated the effect of RTN on the drain current variations as a Model for the introduced FETs. Matsumoto et al. [13, 14] have evaluated the impact of RTN on the CMOS logic circuits for low supply voltages. Compagno et al. [15, 16], Veksl et al. [17], Ling et al. [18] have analyzed the...
reliability of RRAM and Flash memory under the impact of RTN to estimate the accuracy of data loss.

Imamoto et al. [19], Forbes and Miller [20], Chen et al. [21], Ioannidis et al. [22], Pirro et al. [23] have tried to decrease the level of RTN noise by changing some parameters in the structure of MOSFET devices. Although these methods can be effective, they might be so expensive. Thus, they require the nanometer instrument technologies and they are difficult to implement. Islam et al. [24], Seo et al. [25], Kushwaha et al. [26], Tanaka et al. [27] have considered the circuit noise as a deterministic process and have introduced a model based on the oxide trap density and energy level. Gökçen and Demir [28], Mohanty et al. [29] have considered the noise as a non-stationary and stochastic process. For de-noising the drain current from the RTN, some studies have been conducted. Diaz-Fortuny et al. [30, 31] have introduced a method to remove the RTN based on the detection and comparison of trace levels between the fast and slow defects. However, this method is consuming and cannot be implemented for real-time applications. Gao et al. [32], Vaseghi [33], Petrychuk et al. [34], Higashi et al. [35], Tega et al. [32–36] have analyzed and extracted RTN using the Fast Fourier Transform (FFT) and the Short Time Fourier Transform (STFT). However, Fourier analysis cannot determine the short-time variations of signal because it can only decompose the signal to same infinitive sinus and cosine series wherein all of the time information will be removed. Du et al. [37], Principato and Ferrante [38], Hendrickson et al. [39] have employed Wavelet decomposition to separate the data and 1/f noise. They have compared the shape of mother waves and introduced the Haar function as the best Wavelet to decompose the RTN. Then they have employed the universal threshold to de-noise the RTN by the Wavelet thresholding method. However, the Wavelet transform depends on the mother wave function and is not adaptive for every type of signal. Hence, it is not considered as a useful tool. In this paper, Empiricil Mode Decomposition (EMD) method is introduced which is the basis of the adaptive orthogonal functions and can be appropriate for non-stationary signals. This method is applied to diverse RTN signals and its capability is shown in decomposing the desired and undesired data.

2. METHOD

In this section, the proposed method for RTN signal is introduced.

2.1. Empirical Mode Decomposition In recent years, Empirical Mode Decomposition has been considered as one of the most practical and efficient approaches in signal processing area. As opposed to the Wavelet and FFT which use the specific orthogonal parametric basis, this method decomposes the signal based on the signal harmonics and is completely adaptive. Therefore, it has a strong capability to decompose non-stationary signals. This method creates some Intrinsic Mode Functions (IMFs) and a residual signal. The procedure to produce the IMFs is based on the subtraction of the baseline function from the main signal. The process continues until the residual signal becomes constant. Baseline function is considered as the average of local extremum of the signal. The IMFs must satisfy the two following conditions:

1. The number of the extremums and zero-crossings must be equal or differ by at most one.
2. In each point, the average value of the defined envelope by the local extremums must be zero. In another word, IMFs must be symmetric functions around zero.

The algorithm can be considered as follow:

1. Find the upper and lower envelopes of the signal x(t).
2. Subtract the average of envelopes (m(t)) from the signal (d(t)=x(t)-m(t)).
3. If d(t) can satisfy the two conditions of IMFs, d(t) can be saved as the first mode, otherwise re-calculate the algorithm from the 1st step for d(t).

Then, the residue signal r(t) obtained from the subtraction of the signal x(t) and the IMF1 is considered to calculate the next modes.

To obtain the next residue, the current IMF must be subtracted from the previous residue which will be employed to obtain the mode. The summery of these relations are

\[ r_1 = \text{IMF}_2 = r_2 \]
\[ r_2 = \text{IMF}_3 = r_3 \]
\[ \cdots \]
\[ r_{n-1} = \text{IMF}_n = r_n \]

whenever the residue r does not have any extremum point with almost the uniform behavior, the algorithm will be finished.

Finally, the input signal x(t) can be expressed as the summation of the IMFs and a residue

\[ x(t) = \sum_{i=1}^{n} \text{IMF}(i) + r(t) \],

where n is the number of decomposition levels and r(t) is the residual signal at the end of the algorithm [40–43]. EMD method can be summarized in Figure 1.

This method is applied to show the decomposed levels on an actual noisy RTN in Figure 2.

For the first stage, because of the adaptive decomposition of EMD, we can propose the EMD thresholding instead of the Wavelet thresholding. Another approach is that we can employ some weights for the decomposed modes since it is clear that our desired data has not been distributed in all IMFs uniformly.
3. RESULTS

We considered two types of signals for our evaluation. Firstly, the actual signal which is extracted from an nMOSFET with Width = 0.16 μm and Length = 2 μm, which was biased by \( V_{GS} = 2.2 \) V, in temperature of 50 °C based on the Measure-Stress-Measure (MSM) method and secondly, the artificial signal which is obtained from a stochastic defect modeling based on the Markov chain to simulate the RTN signal according to Grasser [44]. For the validation of our proposed methods, we applied our methods on the artificial and actual RTN signals.

For the EMD thresholding, six levels of IMFs were extracted and then the method is applied by using the Universal thresholding and soft removing. The Wavelet transform using the Haar function with six levels is used in accompany with the Universal thresholding in this method. For the weighted EMD method, we analyzed the different combinations of IMFs to see which IMF is more similar to the pure data and has higher SNR. Table 1 shows these results.

It is clear that the last IMFs are more related to the pure RTN. The results in Table 1 were obtained for noisy RTN with zero SNR. By analyzing, we understand that some IMFs have less similarity to the pure RTN and have less SNR when considered alone. However, if we add it to other IMFs, we obtain a higher SNR. Therefore, removing an IMF would not be correct and we should better consider a weight for each of the decomposed levels as below.

\[
S = a^*IMF_1 + b^*IMF_2 + c^*IMF_3 + d^*IMF_4 + e^*IMF_5 + f^*IMF_6 + g^*r
\]  

(3)

For the next stage, we employed an optimization method to reach a reasonable weights for 1000 RTN signals to reach the highest level of SNR. The input data were selected from diverse signal records with different levels of noise. The data were collected in an excel file and based on the genetic optimization algorithm with 0.8 mutation, the data were processed one by one in MATLAB software. In Table 2 the weight results are presented.

Finally, all of the mentioned methods are evaluated, and samples of this analysis have been shown for artificial and actual RTNs in Figure 3 and Figure 4 respectively.

For a better evaluation, three indicators, namely, SNR, Mean Square Error (MSE) and Percent Root mean square Difference (PRD) are calculated for the different methods.

\[
SNR = 10 \log \left( \frac{\sum_{i=1}^{N} x_i^2(t)}{\sum_{i=1}^{N} (x(t) - \bar{x}(t))^2} \right)
\]  

(4)

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} (x(t) - \bar{x}(t))^2
\]  

(5)
TABLE 1. SNR for different combination of IMFs

| IMFs | 1   | 2   | 3   | 4   | 5   | 6   | r  | \( \sum(1:5) \) | \( \sum(1:6) \) | \( \sum(2:r) \) | \( \sum(3:r) \) | \( \sum(4:r) \) | \( \sum(5:r) \) | \( \sum(6:r) \) |
|------|-----|-----|-----|-----|-----|-----|----|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| SNR  | 1.3347 | 0.2310 | 1.6905 | 2.3212 | 2.9312 | 3.7918 | 4.1381 | 1.9105 | 4.8234 | 4.2648 | 5.3968 | 5.2189 | 4.4283 |

TABLE 2. Weights for the different decomposed levels

| Factor | a    | b    | c    | d    | e    | f    | g    |
|--------|------|------|------|------|------|------|------|
| Value  | 0.0291 | 0.0467 | 0.3277 | 0.2809 | 0.5297 | 0.7384 | 0.9271 |

\[
PRD = 100 \left( \frac{\sum_{i=1}^{N} (\hat{x}(t) - x(t))^2}{\sum_{i=1}^{N} x^2(t)} \right)
\]

where \( x(t) \) is the clean signal and \( \hat{x}(t) \) is the de-noised signal.

The results of SNR, MSE and PRD have been reported for the mentioned method for the various SNRs in different RTNs in Tables 3, 4 and 5 respectively. The results were obtained by averaging on 50 simulations. By considering an indicator to evaluate the improvement rate of the methods, we can define

\[
\text{Indicator} \% = \frac{\sum_{i=1}^{n} \text{SNR}_{EMD} - \sum_{i=1}^{n} \text{SNR}_{DWT}}{\sum_{i=1}^{tN} \text{SNR}_{DWT}} \times 100
\]

where \( tN \) is the number of the calculated SNRs. This indicator can be utilized as well for the MSE and PRD to evaluate the results.

Summary of the results is shown in Figure 5. The results show 14%, 27% and 19% improvement in SNR, MSE and PRD for the EMD Thresholding, respectively. The results also show 54%, 61% and 39% improvement in SNR, MSE and PRD for the Weighted EMD, respectively.

In other side, we should consider the pros and cons of the proposed method.

**TABLE 3. SNR results for the mentioned methods**

| Input SNR (db) | -5 | 0  | -2.5 | 5   | 10  |
|----------------|----|----|------|-----|-----|
| Method         |    |    |      |     |     |
| Wavelet Thresholding [39] | -2.141 | 2.3456 | 4.2704 | 6.8205 | 10.6842 |
| EMD Thresholding | -1.034 | 3.0356 | 4.8875 | 7.2971 | 11.0345 |
| Weighted EMD    | 1.629 | 5.1352 | 6.1970 | 8.3557 | 12.5159 |
The computation time of the methods are evaluated in MATLAB by “tic toc” command and the average of the 50 runs of the algorithms is shown in Table 6. In order to obtain the computation time, we have employed a laptop with 2.2 GHz CPU clock frequency.

According to the results, Wavelet thresholding has the least computational time among the other methods, which is about 38 times faster than the weighted EMD method. However, the denoising approach is usually analyzed after recording the data as an off-line processing. Furthermore, the cost of computation in the range of around one second will not be a critical challenge and the denoising performance would be more significant than the computational time.

The bottle neck of the weighted EMD would be the process of finding the weights using diverse signals with different levels before denosing. It is noteworthy that the only bottle neck of this approach is finding appropriate weights.

3.1. RTN Intensity Indicator

Having de-noised the RTN signals, we can consider a criterion for finding out the energy level of RTNs to show the intensity of this phenomenon. In that regard, we can make use of the following equation.

\[ I = \int_{t_0}^{t_1} s(t) dt \]  \hspace{1cm} (8)

where \( I \) is the intensity, \( s(t) \) is the de-noised RTN signal and \( (t_0,t_1) \) is the desired interval. It is clear that de-noising would be necessary as sometimes noise might have a considerable intensity and it could potentially make an error.

This way, we can find out the quality and rate of the reliability for digital circuits. Therefore, one of the indicators to make comparison among the different circuits would be the intensity (I) of RTN and we can measure the circuits in diverse situations and capture RTNs to compare the reliability rate.

4. CONCLUSION

One of the most suitable analysis methods for RTNs as a non-stationary signal is EMD. In this paper, this tool and its application were introduced and a comparison among the existing methods was made. Firstly, we proposed the EMD thresholding method that could have a better result compared to the previous methods. Then, we analyzed the intrinsic modes for RTN and found the last modes are more similar to our desired data compared to the earlier modes. Therefore, we proposed to weight the modes in order to extract the pure RTN. The results show 14%, 27% and 19% improvement in SNR, MSE and PRD for the EMD Thresholding, respectively. Furthermore, the results also show 54%, 61% and 39% improvement in SNR, MSE and PRD for the weighted EMD, respectively.

### Table 4. MSE results for the mentioned methods

| Input SNR (db) | Method                  | MSE   |
|---------------|-------------------------|-------|
| -5            | Wavelet Thresholding [39]| 0.0281|
| 0             | Wavelet Thresholding [39]| 0.0145|
| -2.5          | Wavelet Thresholding [39]| 0.0092|
| 5             | Wavelet Thresholding [39]| 0.0064|
| 10            | Wavelet Thresholding [39]| 0.0043|
| -5            | EMD Thresholding         | 0.0105|
| 0             | EMD Thresholding         | 0.0061|
| -2.5          | EMD Thresholding         | 0.0047|
| 5             | EMD Thresholding         | 0.0026|
| 10            | EMD Thresholding         | 0.0007|

| Input SNR (db) | Method                  | PRD   |
|---------------|-------------------------|-------|
| -5            | Wavelet Thresholding [39]| 98.21 |
| 0             | Wavelet Thresholding [39]| 70.44 |
| -2.5          | Wavelet Thresholding [39]| 56.75 |
| 5             | Wavelet Thresholding [39]| 42.11 |
| 10            | Wavelet Thresholding [39]| 36.08 |
| -5            | EMD Thresholding         | 74.56 |
| 0             | EMD Thresholding         | 56.92 |
| -2.5          | EMD Thresholding         | 43.67 |
| 5             | EMD Thresholding         | 38.22 |
| 10            | EMD Thresholding         | 32.14 |
| -5            | Weighted EMD            | 58.17 |
| 0             | Weighted EMD            | 38.58 |
| -2.5          | Weighted EMD            | 33.71 |
| 5             | Weighted EMD            | 28.45 |
| 10            | Weighted EMD            | 25.67 |

### Table 6. Computation time of the mentioned methods

| Method                  | Computation-Time (s) |
|-------------------------|----------------------|
| Wavelet Thresholding [39]| 0.023246599          |
| EMD Thresholding         | 1.152699315          |
| Weighted EMD             | 0.902714652          |

**Figure 5.** The results of SNR, MSE and PRD for three methods and in terms of different input SNRs
5. ACKNOWLEDGEMENT
The authors would like to thank the Austrian Research Promotion Agency FFG, Institute for Microelectronics in TU-Wien and specially Dr. Tibor Grasser and Dr. Michael Waltl for their support in this research.

6. REFERENCES
1. Connelly, J. A., Low-Noise Electronic System Design, Guide Books, (1993), John Wiley & Sons, Inc.
2. Li, Z., Sui, N., and Wang, G., "Experimental study on vibration and noise of pure electric vehicle (PEV) drive systems", International Conference on Electric Information and Control Engineering, ICEICE 2011 - Proceedings, (2011), 5914–5917. doi:10.1109/ICEICE.2011.5776874
3. Roshanian, J, Khaksari, H, Khoshnood, A. M., and Hasan, S. M., "Active Noise Cancellation using Online Wavelet Based Control System: Numerical and Experimental Study", *International Journal of Engineering, Transactions A: Basics*, Vol. 30, No. 1, (2017), 120–126. doi:10.5829/idosi.ije.2017.30.01a.15
4. Grasser, T., Rott, K., Reisinger, H., Waltl, M., Franco, J., and Kaczor, B., "A unified perspective of RTN and BTT", *IEEE International Reliability Physics Symposium Proceedings*, (2014), 126. doi:10.1109/IRPS.2014.6860483
5. Valinataj, M., "Reliability and Performance Evaluation of Fault-aware Routing Methods for Network-on-Chip Architectures", *International Journal of Engineering, Transactions A: Basics*, Vol. 27, No. 4, (2014), 509–516. doi:10.5829/idosi.ije.2014.27.04a.01
6. Karatson, T. A., Pastorek, M., Theodorou, C. G., Fadlje, A., Wichmann, N., Desplanque, L., Wallart, X., Bollaert, S., Dimitriadis, C. A., and Ghibaudou, G., "Static and low frequency noise characterization of ultra-thin body InAs MOSFETs", *Solid-State Electronics*, Vol. 143, (2018), 56–61. doi:10.1016/j.sse.2017.12.001
7. Stampfer, B., Zhang, F., Illarionov, Y. Y., Knobloch, T., Wu, P., Waltl, M., Grill, A., Appenzeller, J., and Grasser, T., "Characterization of Single Defects in Ultrascaled MoSi2 Field-Effect Transistors", *ACS Nano*, Vol. 12, No. 6, (2018), 5368–5375. doi:10.1021/acsnano.8b00268
8. Waltl, M., Wagner, P. J., Reisinger, H., Rott, K., and Grasser, T., "Advanced data analysis algorithms for the time-dependent defect spectroscopy of NBTI", *IEEE International Integrated Reliability Workshop Final Report*, (2012), 74–79. doi:10.1109/IRW.2012.6460924
9. Jech, M., Ullmann, B., Rzepe, G., Tyaginov, S., Grill, A., Waltl, M., Jabs, D., Jungemann, C., and Grasser, T., "Impact of Mixed Negative Bias Temperature Instability and Hot Carrier Stress on MOSFET Characteristics - Part II: Theory", *IEEE Transactions on Electron Devices*, Vol. 66, No. 1, (2019), 241–248. doi:10.1109/TED.2018.2873421
10. Lai, Y., Li, H., Kim, D. K., Diroll, B. T., Murray, C. B., and Kagan, C. B., "Low-frequency (1/f) noise in nanocrystal field-effect transistors", *ACS Nano*, Vol. 8, No. 9, (2014), 9664–9672. doi:10.1021/nn503033b
11. Ullmann, B., Jech, M., Puchkarsky, K., Rott, G. A., Waltl, M., Illarionov, Y., Reisinger, H., and Grasser, T., "Impact of Mixed Negative Bias Temperature Instability and Hot Carrier Stress on MOSFET Characteristics - Part I: Experimental", *IEEE Transactions on Electron Devices*, Vol. 66, No. 1, (2019), 232–240. doi:10.1109/TED.2018.2873419
12. Feng, W., Dou, C. M., Niwa, M., Yamada, K., and Ohmori, K., "Impact of random telegraph noise profiles on drain-current fluctuation during dynamic gate bias", *IEEE Electron Device Letters*, Vol. 35, No. 1, (2014), 3–5. doi:10.1109/LED.2013.2288981
13. Matsumoto, T., Kobayashi, K., and Onodera, H., "Impact of random telegraph noise on CMOS logic delay uncertainty under low voltage operation", *Technical Digest - International Electron Devices Meeting, IEDM*, (2012).
14. Matsumoto, T., Kobayashi, K., and Onodera, H., "Impact of random telegraph noise on CMOS logic circuit reliability", Proceedings of the IEEE 2014 Custom Integrated Circuits Conference, CICC 2014, (2014), Institute of Electrical and Electronics Engineers Inc. doi:10.1109/CICC.2014.6945997
15. Compagnoni, C. M., Ghidotti, M., Lacaita, A. L., Spinelli, A. S., and Visconti, A., "Random telegraph noise effect on the programmed threshold-voltage distribution of flash memories", *IEEE Electron Device Letters*, Vol. 30, No. 9, (2009), 984–986. doi:10.1109/LED.2009.2026658
16. Compagnoni, C. M., Spinelli, A. S., Belmonti, S., Bonanomi, M., and Visconti, A., "Cycling effect on the random telegraph noise instabilities of NOR and NAND flash arrays", *IEEE Electron Device Letters*, Vol. 29, No. 8, (2008), 941–943. doi:10.1109/LED.2008.2009964
17. Vekslers, D., Bersuker, G., Vandelili, L., Povodiani, A., Larcher, L., Muraviev, A., Chakrabarti, B., Vogel, E., Gilmer, D. C., and Kirsch, P. D., "Random telegraph noise (RTN) in scaled RRAM devices", *IEEE International Reliability Physics Symposium Proceedings*, (2013), doi:10.1109/IRPS.2013.6532101
18. Ling, Y. G., Wang, W. Z., Fang, Y. C., Kang, J., Wu, L. D., Yang, Y. C., Cai, Y. M., and Huang, R., "RTN impacts on RRAM-based Nonvolatile logic circuit", 2018 14th IEEE International Conference on Solid-State and Integrated Circuit Technology, ICSICT 2018 - Proceedings, (2018), Institute of Electrical and Electronics Engineers Inc. doi:10.1109/ICSICT.2018.856665
19. Imamoto, T., Ma, Y., Muraguchi, M., and Endoh, T., "Low-frequency noise reduction in vertical MOSFETs having tunable threshold voltage fabricated with 60nm CMOS technology on 300mm wafer process", *Japanese Journal of Applied Physics*, Vol. 54, No. 4, (2015), doi:10.7567/JJAP.54.04DC11
20. L. Forbes and D.A. Miller. Reduction of random telegraph signal (RTS) and 1/f noise in silicon MOS devices, circuits, and sensors. U.S. Patent 8,513,102, (2013).
21. Chen, X., Chen, S., Hu, Q., Zhang, S. L., Solomon, P., and Zhang, Z., "Device noise reduction for silicon nanowire field-effect Transistor based sensors by using a schottky junction gate", *ACS Sensors*, Vol. 4, No. 2, (2019), 427–433. doi:10.1021/acssensors.8b01394
22. Ioannidis, E. G., Leisenberger, F. P., and Enichlmair, H., "Low frequency noise investigation of n-MOSFET single cells for memory applications", *Solid-State Electronics*, Vol. 151, (2019), 36–39. doi:10.1016/j.sse.2018.10.016
23. Pirro, L., Zimmerhackl, O., Zaka, A., Mülner-Mesklamp, L., Nelluri, R., Herrman, T., Cortes-Mayol, I., Hruschka, A., Otto, M., Nowak, E., Mittal, A., and Hoentschel, J., "RTN and LFN noise performance in advanced FDSOI technology", *European Solid-State Device Research Conference*, Vols 2018-September, (2018), 254–257. doi:10.1109/ESSDERC.2018.8486917
24. Islam, A. K. M. M., Oka, M., and Onodera, H., "Measurement of temperature effect on random telegraph noise induced delay fluctuation", *IEEE International Conference on Microelectronic Test Structures*, Vols 2018-March, (2018), 210–215, Institute of Electrical and Electronics Engineers Inc., 210–215. doi:10.1109/CMCTS.2018.8338301
25. Seo, Y., Woo, C., Lee, M., Kang, M., Jeon, J., and Shin, H., "Improving BSIM Flicker Noise Model", 2019 IEEE Electron Devices Technology and Manufacturing Conference, EDMT 2019.
چکیده

نویز تلگرافی تصادفی (RTN) یکی از سیگنالهای بالعمر خاص در دیجیتال دستگاه‌ها است که باعث عوامل سرمناسی‌های مصرفی می‌گردد. استفاده و استخراج منشأهای تلگرافی تصادفی (EMD) در دستگاه‌های مصرفی می‌تواند به دست آورن مدلهای بهینه‌ای برای روش‌های درمانی نویز تلگرافی تصادفی کمک کند. 

مقدمه

RTN یکی از سیگنال‌های بالعمر خاص در دستگاه‌های دیجیتال می‌باشد که باعث عوامل سرمناسی مصرفی می‌گردد. استفاده و استخراج منشأهای RTN می‌تواند به دست آورن مدلهای بهینه‌ای برای روش‌های درمانی نویز تلگرافی تصادفی کمک کند.

نتایج

RTN یکی از سیگنال‌های بالعمر خاص در دستگاه‌های دیجیتال می‌باشد که باعث عوامل سرمناسی مصرفی می‌گردد. استفاده و استخراج منشأهای RTN می‌تواند به دست آورن مدلهای بهینه‌ای برای روش‌های درمانی نویز تلگرافی تصادفی کمک کند.