A new method to analyze Random Telegraph signals in resistive RAMs

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A new technique to analyze Random Telegraph Noise (RTN) is proposed. It has been used
for the analysis of current versus time measurements performed on Ni/HfO₂/Si-n+-based

resistive random access memories (RRAMs). The method allows to study current-time traces with a massive number of data without losing the capability of dealing with background noise and discriminating the active defects responsible for current fluctuations. A comparison of this algorithm with previous ones is given in terms of computing time and RTN description accuracy. The computing efficiency and the validity of the model have been proved and, therefore, it is feasible to propose applications for real time analysis making use of this new algorithm.

I. INTRODUCTION

The next-generation of non-volatile memory technologies is getting wide attention among electronics manufacturers and the scientific community. The expected high-performance and cost-effective features of these emerging non-volatile memories will simplify memory hierarchy and incorporate non-volatility in logic circuits¹⁻⁷. In addition, they will open paths for novel applications in neuromorphic computing and hardware security landscapes^{3,8,9}. Among the technologies available for non-volatile memories, resistive random access memories (RRAMs) are promising devices due to their potential for scalability, low power operation, fast operation, high endurance, their CMOS compatibility and the possibility to be stacked in 3D architectures¹⁻⁵. These features will be essential to introduce RRAMs in industrial production lines, which are focused by the growing prominence of mobile devices and the popularity of Internet-of-things (IoT).

A resistive memory consist of two electrodes made out of a metallic or highly doped semiconductor material that are separated by a dielectric material that can be fabricated by different types of oxides and even 2D materials. Research on these devices has been intensive in the last few years and dozens of devices have been analyzed where the materials employed for the electrodes and dielectric are different.

Although RRAM technology has been successfully employed at the integrated circuit level in a promising manner¹⁰⁻¹², some issues still exist that have to be urgently improved in order to introduce this technology in mass production channels. Variability and reliability have to be addressed. In addition, in order to assist design efforts in an industrial context, Electronic Design Automation (EDA) tools are needed. This implies the development of physical simulators¹³⁻²²,

and reliable compact models for circuit design^{3,23-29}. Recent reviews can be found in references^{5,30}.

Filamentary conduction is assumed to be the most common physical mechanism behind resistive switching (RS) in most of the RRAMs found in the literature. The formation and destruction of conductive filaments (CFs) inside the insulating layer permits the differentiation of two resistive states that allow the codification of the logic level for memory applications. Nevertheless, the presence of single or multiple traps inside or close to the conductive filaments can strongly influence the charge conduction giving rise to current fluctuations (named random telegraph noise, RTN) with relative larger amplitudes in the high-resistance state (HRS) than in the low-resistance state (LRS)^{31,32}. In memory applications, these fluctuations can cause severe operation or read errors. On the other hand, this RTN fluctuations in resistive RAMs can be used as an entropy source of random number generators³³⁻³⁵.

Different methods have been employed to characterize RTN³⁶⁻³⁹. In this context, an in-depth description of RTN signals is needed to unveil the contribution of defects responsible for the current fluctuations from the presence of background noise. Some of the previously proposed techniques can deal with this task³⁷⁻³⁹, but if long traces are under consideration these algorithms might be too expensive in terms of computing time because they need to sweep all the data in the current-time ($I-t$) trace several times.

In this contribution, we present a new method to analyze RTN signals, the Locally Weighted Time Lag Plot (LWTLP). This new method (see the details in section II) allows to reduce the computing time with respect to previous ones, being also an accurate technique that allows to perform a useful analysis as in the case of previous procedures³⁶⁻³⁷. The usefulness of the new method will be demonstrated for ($I-t$) traces with more than one million data points.

The paper is organized as follows. In Section II, a brief review of previous techniques for analyzing RTN signals is presented and our new proposal, the LWTLP method, is detailed. In Sec. III, the fabricated devices and measurement set-up are described. In Sec. IV, we present the main results and the corresponding discussion. Finally, the conclusions are drawn in Sec. V

II. LOCALLY WEIGHTED TIME LAG PLOT TECHNIQUE

The Time Lag Plot (TLP) is a technique used to visualize RTN data³⁶. Given a set of N data points of a current versus time trace, (I_i, t_i) , with $i \in [1, N]$, the current value at a certain moment, I_{i+1} , is plotted versus the previous current, I_i . In this way, stable current values appear as clusters of points along the diagonal of the graph ($I_{i+1} = I_i$), while transitions between current levels show up outside this diagonal. The proximity of two stable levels and/or the background noise can produce the overlapping of point clusters, making the interpretation of the plot difficult³⁷⁻⁴⁰. Furthermore, the TLP does not provide a quantitative direct information about the number of points concentrated (or even overlapped) around a given plot region of the TLP space (for stable levels, this information would be related to the probability of measuring a particular current linked to these states). In order to overcome these drawbacks, alternative time lag plots have been proposed, among them, the Radius Time Lag Plot (RTLP)³⁹ and the Weighthed Time Lag Plot (WTLP)^{37,38,41}. On the one hand, considering the RTLP method, the value associated to a given position (I_i, I_{i+1}) depends on the number of counts in the neighborhood (within a region described by a given radius). In that way, the zones with a higher concentration of points in the space are highlighted. On the other hand, the WTLP method calculates the occurrence probability in a given position of the space taking into consideration the occurrences in the rest of positions in the graph by

means of the bidimensional Gaussian distribution (BGD)^{37,38,41}. That is, for each position, the probability is calculated as a weighted sum of all the sampled data. The weights are given by the distance to each occurrence and the corresponding value of the BGD. In that way, both methods (RTLP and WTLP) add information about the probability of occurrence in a third axis and, therefore, overcome the problem related to the hidden occurrence levels because of background noise. However, both techniques are computationally expensive. This is not the case for the technique we present here, the locally weighted time lag plot (LWTLP) method. In this new technique, the probability at a given position (I_i, I_{i+1}) is calculated also taking into account the distance to the counts in other positions (by means of a BGD), but only if those positions are close to the considered position (I_i, I_{i+1}) . Hence, not all the plot domain is considered (as in the WTLP method), but only the neighborhood to each point of the space (as in the RTLP method). In that sense, the LWTLP technique holds the best features of both methods.

Given N data points, (I_i, t_i) (with $i \in [1, N]$), the LWTLP method reduces the data space (I_i, I_{i+1}) of a trace to a $M \times M$ matrix ($M < N$), as in the WTLP case³⁷⁻³⁸. Each pair of values (I_i, I_{i+1}) is linked to the corresponding matrix cell (indexed by the pair of variables $(\hat{x}, \hat{y})$). The number of events associated to this position are counted and also the neighbor sites of the matrix are updated with each event. These latter values are weighted by a function dependent on the distance to the point considered in each calculation. In our study, the neighbor regions considered for the calculation of the occurrence probability are described by 3×3 or 5×5 sub-matrices (a choice to be made at the beginning of the analysis). A more detailed algorithm description is given below.

The Locally Weighted Time Lag Plot method is based on the following procedure. First of all, the space (I_i, I_{i+1}) is reduced to $M \times M$ points (x, y) , by means of equations (1) and (2):

$$x = \frac{\hat{x}}{M-1}(I_{max} - I_{min}) + I_{min} \quad (1)$$

$$y = \frac{\hat{y}}{M-1}(I_{max} - I_{min}) + I_{min} \quad (2)$$

where $\hat{x}$ e $\hat{y}$ are the indices of the matrix of values to be displayed ($\hat{x} = 0, 1, \dots, M-1$ $\hat{y} = 0, 1, \dots, M-1$) and I_{max} e I_{min} are the maximum and minimum current values used in the plot. The current interval that each matrix cell represents is determined by:

$$\Delta x = \Delta y = \frac{I_{max} - I_{min}}{M} \quad (3)$$

Once the matrix has been determined, for each of the $N-1$ pairs of points (I_i, I_{i+1}) of the experimental current trace, their coordinates $\hat{x}, \hat{y}$ are calculated:

$$\hat{x} = \text{int} \left(\frac{I_i - I_{min}}{\Delta x} \right) \quad (4)$$

$$\hat{y} = \text{int} \left(\frac{I_{i+1} - I_{min}}{\Delta y} \right) \quad (5)$$

where $\text{int}(x)$ is the function that returns the integer closest to x . Once the coordinates $(\hat{x}, \hat{y})$ are known, the matrix is updated, considering not only the corresponding cell, but also the surrounding coordinates. For this latter action, two alternatives are offered (see Figure 1):

WL5TLP: the nearest cells (until a maximum change of the indices in 2 units from the central cell $\hat{x}, \hat{y}$) are taken into account (Figure 1b), which constitutes a 5×5 matrix centered on $(\hat{x}, \hat{y})$.

The matrix values are updated with weights following a two-dimensional Gaussian distribution depending on the normalized distance between cells (see Figure 1b). That is:

$$WL_5TLP(x, y) = WL_5TLP(x, y) + d_k, \quad (6)$$

where the index k takes values from 0 to 5 ($k=0$ for the central cell $(\hat{x}, \hat{y})$ and k grows as shown in Figure 1b). The values of d_k are shown in Table I.

WL3TLP. It is a simplified version of the former case. Only the adjacent cells are considered, this option constitutes a 3×3 matrix centered on $(\hat{x}, \hat{y})$ (see Figure 1a). The weight values of the nine cells (d_0, d_1 and d_2) are shown in Table I.

Finally, once the calculations are performed, the matrix values are normalized.

FIG. 1. Schema of the matrix cells updated for each event linked to the cell $(\hat{x}, \hat{y})$. Two cases have been considered: WL3TLP, only the adjacent cells are taken into account (a); WL5TLP, the 5×5 sub-matrix centered in $(\hat{x}, \hat{y})$ is calculated (b). The weight values ($d_k, k = 0..5$) are shown in Table I.

TABLE I. Weights used in the LWTLP technique (with $\sigma_f = 1.5$)

	d_0	d_1	d_2	d_3	d_4	d_5
$f(a) = e^{-\frac{a^2}{2\sigma_f^2}}$	$f(0)$	$f(1)$	$f(\sqrt{2})$	$f(2)$	$f(\sqrt{5})$	$f(2\sqrt{2})$
Value	1	0.8007	0.6412	0.4111	0.3292	0.1690

III. DEVICE FABRICATION AND MEASUREMENT

A. Device Description

Ni/HfO₂/Si devices were fabricated on (100) n-type CZ silicon wafers with resistivity (7-13) mΩ·cm following a field isolated process. The 20nm-thick HfO₂ layers were deposited by Atomic Layer Deposition at 498K using TDMAH and H₂O as precursors and N₂ as purge and carrier gas. The resulting structures are square cells of 5×5μm². A schematic cross-section of the final device is shown in the inset of Figure 2. More detailed information about the process flow can be found in References 42 and 43.

B. Characterization Setup

The current in both resistive states was recorded in the time domain using a HP-4155B semiconductor parameter analyzer. The voltage was applied to the top Ni electrode, while the Si substrate was grounded. Both the I-V curves for the forming process and RS cycles were measured making use of ramped voltage signals (some set and reset curves are shown in Figure 2). RTN data were measured in the high resistance state (HRS) of the devices employing different biases during observation periods of several seconds (thousands of data were obtained for each measurement series). The RTN signals were recorded by an automatic algorithm that considers the previous measured data making use of a smart procedure (a Matlab® software tool was employed to control the instrumentation). This algorithm could request to continue the RTN measurement or to measure a new voltage or switching cycle when the measured current values are not optimal for the detection of RTN traces. Figure 3 shows a long register of 1.2 million data points obtained at -0.5V for 6800 seconds and the detail of a time period of 100 seconds (where typical RTN signals can be recognized by current fluctuations between different levels).

FIG. 2. (Color online) Current-voltage characteristics during typical set and reset cycles with a current compliance of 100 μ A. Inset: schematic cross-section of the device structure.

FIG. 3. (Color online) Current versus time plot measured at an applied voltage of -0.5V for 6800 seconds (1.2 million of samples were recorded). A detail of a time period of 100 seconds is shown, where RTN signals are apparent.

IV. RESULTS AND DISCUSSION

As explained before, in order to characterize RTN signals, several techniques have been used, such as the Time Lag plot (TLP) and the Weighted Time Lag Plot (WTLP) methods^{36-38,41}.

The TLP representation method allows identifying the current levels present in a RTN signal when the number of data measured in the traces is low. As the amount of data rises, TLP shows a populated point cloud from which no clear information can be extracted. Furthermore, in the case of close current levels, clusters of points in the diagonal could overlap because of the background noise (see Figure 4a), leading to overlapping stretched clusters instead of rounded clusters⁴⁰. To improve this technique, the RTLP and WTLP were proposed^{37,39}, adding information about the occurrence probability in a third axis (a Z axis), see Figure 4b and Figure 4c, as an example. Finally, in Figure 4d, the results of the proposed new LWTLP technique are shown for the same experimental samples.

Figures 4 and 5 show the time-lag plots of two RTN sequences of 2000 samples using the four methods analyzed in this study (the corresponding I - t traces can be seen in Reference 40, Table I, cell (6,1) and cell (5,1), respectively).

FIG. 4. (Color online) RTN plots for the RTN signals shown in Reference 40 (Table I, row 6). Trap density variations lead to irreversible changes in the current levels. The trace consists of 2000 data points measured at an applied voltage of - 0.28V on a RRAM in HRS. a) Time Lag Plot, b) RTLP, c) WTLP and d) LWTLTP with a 5×5 matrix of neighbor points and $M = 400$.

FIG. 5 (Color online) RTN plots for the case of activation and deactivation of two stable RTN signals. The corresponding I - t RTN signals and the physical interpretation are shown in Reference 40 (Table I, row 5). The trace consists of 2000 data points measured at an applied voltage of - 0.62V. a) Time Lag Plot, b) RTLP, c) WTLP and d) LWTLTP with a 5×5 matrix of neighbor points and $M = 400$.

In order to shed light on the results plotted in Figure 5, and to evaluate the accuracy of the new methodology, we have compared the results of the RTLP, WTLP and LWTLTP methods by extracting the coordinates of points p_1 to p_6 (see Figure 5a) in the TLP domain. They

correspond to the location of the TLP cloud points where the higher occurrence probabilities are placed (Table II).

TABLE II. Evaluation of the regions of higher occurrence probability making use of the RTLP, WTLP and LWTLP (5x5 matrix) procedures (data corresponding to Figure 5 where the most populated regions in the TLP domain (p_1 - p_6) are assumed as a reference).

		RTLP	WTLP	LWTLP
p_1	$I_i(nA)$	168.3±1.8	167.9±1.1	168.1±1.5
	$I_{i+1}(nA)$	168.2±1.8	167.9±1.1	168.1±1.5
p_2	$I_i(nA)$	109.7±1.9	109.7±0.6	109.9±0.85
	$I_{i+1}(nA)$	109.7±1.9	109.7±0.6	109.9±0.85
p_3	$I_i(nA)$	169.2±3.8	168.9±0.6	168.9±0.6
	$I_{i+1}(nA)$	140.9±1.2	140.3±0.6	140.3±0.6
p_4	$I_i(nA)$	140.9±1.2	140.3±0.6	140.3±0.6
	$I_{i+1}(nA)$	169.2±3.8	168.9±0.6	168.9±0.6
p_5	$I_i(nA)$	196.9±2.1	197.6±0.7	197.6±0.5
	$I_{i+1}(nA)$	110.5±2.3	109.7±0.6	109.7±0.5
p_6	$I_i(nA)$	110.5±2.3	109.7±0.6	109.7±0.5
	$I_{i+1}(nA)$	196.9±2.1	197.6±0.7	197.6±0.5

It can be seen (Table II) that the capacity to determine the regions where the higher occurrence probabilities are located for the LWTLP method is as good as in the other two

methods. This new method is especially useful when the number of samples is high. Figure 6 shows a trace of 1.2 million samples recorded at - 0.5V for 10500 seconds. The Locally Weighted Time Lag Plot (LWTLP) has employed 9.6 seconds (with $M=400$ and 5×5 matrix of neighbor points), while an equivalent representation of probability by means of the WTLP would require an estimated computation time of 11.5 hours.

FIG. 6. (Color online) a) I - t trace of 1.2 million of samples measured at an applied voltage of - 0.5V for 10500 seconds. b) Corresponding Time Lag Plot of the RTN signal, c) Time Lag Plot obtained by means of the Locally Weighted method (LWTLP). A computation time of 9.6 seconds has been required for the whole data set ($M=400$ and 5×5 neighbor matrices have

been employed). The WTLP method would require an estimated computation time of 11.5 hours for this long I - t trace.

For the sake of comparison, Table III shows the computation times to process these 2000-point signals. As commented above, although the four methods give information on the number of defects and the corresponding current levels, only the RTLP, WTLP and LWTLP represent the probability regions. Furthermore, the latter is much less computationally expensive than the others and, therefore, suitable for real time applications.

TABLE III. Computing time comparison for different RTN analysis methods for a (I-t) trace with 2000 samples. The calculations were performed in a PC with a processor Intel®Core™ I7 Q720 CPU@1.6Ghz. N is the number of samples in the trace, $n \times n$ is the matrix size used in the LWTLP method (where $n \ll M$), and $M \times M$ is the matrix size of discrete (I_i, I_{i+1}) pairs. For the LWTLP we use $N=2000$, $M=400$ and $n=5$.

Method	Reduction of the space (I_i, I_{i+1}) to (x, y) (eqs. (1-2))	Order of complexity	Computation time	Probability	Fitting parameters
TLP	<i>No</i>	$N-1$	$0.31s$	<i>No</i>	<i>No</i>
WTLP	<i>Yes</i>	$(N-1) M^2$	$3.94s$	<i>Yes</i>	<i>Yes</i> (α)
RTLP	<i>No</i>	N^2	$3.68 s$	<i>Yes</i>	<i>Yes</i> (r)
LWTLP	<i>Yes</i>	$(N-1)n^2$	$5.23ms$	<i>Yes</i>	<i>No</i>

Different flavors of this method could be implemented if the 5×5 matrix is increased to 7×7 or 9×9 matrices, or reduced to 3×3 matrices, depending on the accuracy required for a specific application. In these cases, there would be a trade-off between an agile computational implementation and the required accuracy in the occurrence probability description. In line with this consideration, and for the sake of clarity, we have compared the results obtained making use of 3×3 and 5×5 matrices (the I-t data related to Figures 4 and 5 are considered).

The occurrence probabilities are described in a better manner in the 5x5 case at the cost of a slightly higher computation time, as it is shown in Figure 7.

FIG. 7. (Color online) RTN plots for the RTN signals shown in Reference 40 (Table I, row 6). The trace consists of 2000 data points measured at an applied voltage of - 0.28V on a RRAM in HRS. a) LWTLP with a 3×3 matrix of neighbor points, $M = 400$ and computation time 4.9ms. b) LWTLP with a 5×5 matrix of neighbor points, $M = 400$ and computation time 5.23ms. RTN plots for the case of activation and deactivation of two stable RTN signals. The corresponding I - t RTN signals and the physical interpretation are shown in Reference 40 (Table I, row 5). The trace consists of 2000 data points measured at an applied voltage of -

- 0.62V. c) WTLP with a 3×3 matrix of neighbor points, $M = 400$ and computation time 4.9ms.
d) WTLP with a 5×5 matrix of neighbor points, $M = 400$ and computation time 5.23ms.

Finally, it is worth pointing out that in relation to the weights employed in the LWTLTP technique (given in Table I), we have tried different values of the σ_f parameter (Figure 8). We have found that for $\sigma_f=1.5$ a good trade-off is obtained for all the experimental data sets under study. In the LWTP method we can change the σ_f parameter and matrix size, and these two options determine the LWTLTP procedure accuracy. Nevertheless, we have shown that $\sigma_f=1.5$ works reasonably well in all cases and the option to refine accuracy could be just linked to the matrix dimension determination, although 3×3 and 5×5 matrices work well. In this respect, we determine a local weighting approach of the surrounding points in the TLP domain in the LWTLTP. However, in the other plots methods, such as the WTLP, the standard deviation is used to perform the fitting parameter determination since the whole experimental data sequence is considered.

FIG. 8. (Color online) RTN plots for the case of activation and deactivation of two stable RTN signals for different σ_f values and 5x5 matrices (see Table I). a) $\sigma_f = 0.25$, the matrix central point is close to 1 and the others neighboring points are close to zero. The neighbor points scarcely contribute to the plot, b) $\sigma_f = 0.75$, the closest neighbor points slightly contribute, and the maximum occurrence probability regions are highlighted, c) $\sigma_f = 1.5$, a reasonable trade-off between the magnitude of the occurrence probability maxima and the contribution of non-null occurrence probability regions is achieved, d) $\sigma_f = 2.5$, the neighboring points contribute almost the same than the matrix central points.

V. CONCLUSIONS

A new technique to obtain time lag plots of Random Telegraph Noise (RTN) signals has been proposed and applied to I - t traces measured in Ni/HfO₂/Si-n+-based resistive RAMs (RRAMs). As other previously proposed methods (RTLTP and WTLTP), this new technique allows to calculate the probability associated to each position in the (I_i, I_{i+1}) plot, taking also in consideration the occurrences in the neighborhood. However, the computation time is much lower. In this way, the method allows the study of current-time traces with a massive number of data without losing the capability of dealing with background noise and discriminating the presence of active defects responsible for current fluctuations. A comparison of this algorithm with previous ones is given in terms of computing time and RTN description accuracy.

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