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RTS NOISE DETECTION AND VOLTAGE EFFECT ON RTS IN HgCdTe FOCAL PLANE ARRAY

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Abstract: We developed an automated Random Telegraph Signal detection and characterization method, as well as a blinking noise and slow drift separation method adapted to focal plane arrays. Utilizing these methods, a study of the evolution of the number of RTS pixels and the amplitudes of the blinking signal as a function of the reverse bias voltage and temperature is conducted. It is shown that physical characteristics of RTS follow Arrhenius laws and increase with bias. Finally, the origin of the increase of the amplitude as a function of the reverse bias is discussed.

Keywords: Random Telegraph Signal, 1/f noise, Reverse Bias, Image Quality, Algorithm

INTRODUCTION

Temporal noise is one of the main challenges in the quest for high operability and stability of image quality over time in infrared focal plane arrays (IR FPA). This type of noise cannot be corrected by a classical non-uniformity correction, as parasitic extra-noise signal may vary in time. Among the sources of temporal noise, low-frequency noises, or $1/f^\alpha$ noises, with f being the frequency and α a coefficient between 1 and 2, are part of the main sources of noise restraining the high operating temperature trend in cooled infrared sensors. Random Telegraph Signal (RTS) is one of them. It exhibits significant current variations with seemingly random occurrences in the temporal dimension. It can affect small scale image quality when the jump amplitude exceeds the residual fixed pattern noise and the very longterm stability through its impact on gain/offset correction tables. Therefore, understanding the physics behind this phenomenon is critical to improve cooled sensors' image temporal stability.

Also called “blinking pixel” in the frame of FPAs, RTS pixel exhibits a multi-stable signal, i.e. a signal fluctuating between multiple stable states. Figure 1 shows a bi-stable RTS signal recorded on our FPA. It

presents two stable states, separated by a jump characterized by its amplitude A, and with instant lifetimes τ_{up} and τ_{down} . Mean values of lifetimes $\langle\tau_{up}\rangle$ and $\langle\tau_{down}\rangle$ are commonly used to characterize the blinking frequency. In the case of a bi-stable RTS, the relation between the blinking lifetimes and the blinking frequency is as described in Equation (1):

$$f_c = \frac{1}{\langle\tau_{up}\rangle} + \frac{1}{\langle\tau_{down}\rangle} \quad (1)$$

RTS has been detected in many types of systems, such as nanowires [1], silicon transistors [2] and photodectors [3], and IR FPA, such as T2SL [4], InGaAs [5] or HgCdTe [6, 7] detectors. It would be too simplistic to assume that each RTS behavior in each system is a consequence of the same physical phenomenon. Thus, this article is solely discussing of the RTS behavior in HgCdTe detectors. Prior results have been established [6] on this material, proving that the RTS amplitude and lifetimes demonstrated a Boltzmann behavior, which means it is activated by temperature with an activation energy E_a . The objective of our study is to further this study with varying bias voltage, in order to highlight a field effect.

In the first part of this paper, the algorithm of detection and characterization of the RTS pixels is presented. It is based on a changepoint detection method, a corner frequency method and a histogram fit method. The second part is focused on the detection problems raised by the superposition of RTS and other low frequency noises, and the algorithm developed to tackle this issue. Finally, in the third part of the paper, the experimental setup and results on activation energy versus bias on a Mid-Wave Infrared (MWIR) detector are presented.

RTS DETECTION AND CHARACTERIZATION ALGORITHM

The principle of the Algorithm for Advanced RTS Detection (AARD) is presented in figure 2. There are three paths: the changepoint path, also called the “Pruned Exact Linear Time” (PELT) path, the frequency or LFNS one, and the histogram fit one. The changepoint path is based on a changepoint detection called PELT method [8]. It defines a cost function based on the variance of the signal and a threshold for the search in the mean changes. This threshold Cr is designed as follows:

$$Cr = \max(k \cdot MAD(X), \frac{\max(X) - \min(X)}{2k}) \quad (2)$$

with k being the effective tunable threshold, typically varying between 1 and 3, and MAD being the Median Absolute Deviation of the signal X. Having a comparison between two criteria, one on the non-Gaussian

character of the signal, and one on the maximum amplitude of the noise, makes it possible to detect pixels showing a high number of jumps with low amplitudes, as well as pixels showing a low number of jumps with high amplitudes. Then, a State Reduction (SR) algorithm is applied to the extracted signal to compute the final RTS contribution to the raw temporal signal. As shown in [9], the estimated RTS signal is representative of the blinking noise, even with multiple stable states and low RTS-to-white-noise ratio. In the following, the PELT+SR algorithm will be referred simply as PELT.

In parallel, the LFNS and the histogram methods are used to verify the RTS nature and behavior of the pixel. The LFNS method relies on a fit of the power spectral density (PSD) multiplied by the frequency, in order to flatten the $1/f$ noise and highlight the $1/f^2$ noise. It has been shown that the bi-stable RTS noise had a Lorentzian frequency signature [10]. In the LFNS plot, the $1/f$ noise is represented by a constant and the $1/f^2$ or Lorentzian noise shows a peak function which is described by a “Lorentzian times frequency” function as in Equation (3):

$$f.PSD = \Delta I^2 < \tau_{up} >^2 < \tau_{down} >^2 \frac{f_c^2 f}{1 + (2\pi f/f_c)^2} \quad (3)$$

With ΔI the amplitude of the jump, and f_c the corner frequency of the Lorentzian. This corner frequency is extracted, and in the case of bi-stable RTS, this corner frequency is the blinking frequency defined in (1). This study, however, does not focus on frequency characterization, hence this method will only be used in future studies. Finally, the histogram method is based on the histogram plot of the signal, which shows multiple Gaussian distributions if the pixels show RTS with white noise. Fitting these distributions and estimating the difference between consecutive maxima of the fit enable the calculation of the RTS amplitude and the establishment of a “well defined two-level RTS pixels” list, which are the objects of study in the next part of the work. These pixels are characterized by well separated Gaussian distributions, which entail jump amplitudes higher than two times the estimated white noise, and the presence of a minimum between consecutive local maxima of the histogram.

SENSITIVITY OF THE ALGORITHM TO SLOW DRIFT

By using the three methods presented in the previous section, it is possible to detect random telegraph pixels, to estimate and verify their jump amplitude, lifetimes and frequencies, and to extract a list of well-defined two-level pixels. However, despite having low error in the case of pure RTS + white noise, one of the drawbacks of this technique is that it may be sensitive to slow drift, which has a frequency behavior of $1/f^\alpha$, with $1 < \alpha < 2$. In

practice, this drift can be the cause of false detections or high error RTS estimations. An illustration of the effect of the drift on the signal, on the RTS signal estimated with PELT and on its associated histogram is given in Figure 3. We can clearly see an increase of the error in the estimated level number of the RTS signal.

In order to quantify this error, we used a Monte Carlo method to generate different 2 levels RTS signals. Input parameters are mean lifetimes $\langle\tau_{up}\rangle$ and $\langle\tau_{down}\rangle$ (described by an exponential distribution as reported in [11]), jump amplitude A_{RTS} , drift amplitude A_{DRIFT} (we assumed a linear behavior for the present study) and a white temporal noise. After applying PELT method to these signals, we classify our results as follows: a non-detection (ND) is a failure of the algorithm to detect a pixel which is RTS. A false detection (FD) is a detection of a pixel which is not RTS but is detected as such by the algorithm. Finally, a correct detection (CD) is a detection of an RTS pixel as such, and a correct non detection (CND), a detection of a non RTS pixel as such. In this study, fixed input parameters are: the length of the sample, which is 10^4 frames, the white noise considered equal to 10 digits rms (similar to the detector studied in a subsequent section) and the mean lifetimes which are 100 frames. We simulated 10 jump amplitudes ranging from 0 to 200 digits and 6 drift peak-to-peak amplitudes ranging from 0 to 100 digits. For each (A_{RTS}, A_{DRIFT}) condition, we generated 10 distinct RTS signals leading to a total of 600 simulated pixels. First, a preliminary study has been conducted, where the k factor in the Cr criterion is ranging from 0.5 to 3. For pixels without drift, a low k leads to 0% ND and 0% FD and in these cases, PELT is a very robust method. However, when increasing drift, low k brings higher ND and FD percentages than high k, hence this factor needs to be optimized.

We obtained a qualitative color map of the average output of the PELT algorithm as a function of the jump amplitude and drift amplitude, as shown in figure 4a). The color and hashes of each cell correspond to the more probable state (ND, FD, CD or CND) of the 10 distinct RTS signals obtained with the same (A_{RTS}, A_{DRIFT}) condition. On the 600 simulated pixels, we finally obtain 50% FD and 8.9% ND. However, some correct RTS detections are due to the drift and not to the detection of a transition between up and down levels. The corresponding pixels are shown in green cells marked by crosses. They represent 22% of the distribution and present an A_{RTS}/A_{DRIFT} ratio lower than 1. This is consistent with results obtained with the Gaussian method, where 75% of the simulated pixels are detected as “well defined two-level RTS”. In addition, 23% of the RTS pixels (marked by circles) show strong errors between the estimated RTS signal and the raw data. In these cases, high drift systematically increases the estimation errors on the number of levels and/or the jump amplitudes and/or the lifetimes, thus increasing the characterization output error.

In order to reduce the PELT method output error, the Drift And RTS Characterization, Separation by Overall, Unique Level Selection (DARCSOULS) algorithm has been developed to discriminate the blinking signal from the slow drift. The principle of the algorithm is presented in figure 5. It is based on the hypothesis that the amplitude of the drift is negligible over the course of a few RTS jumps. PELT is applied locally on small pieces of the signal. Then the overall number of levels is estimated with the median value of the local number of levels, which allows the compensation of the RTS signal. The drift is calculated by applying a low-pass filter to the remaining signal. Finally, the extracted RTS signal is obtained by subtracting the calculated drift from the raw signal and applying PELT on the overall extracted signal.

An optimization between the computation time, the number of slices according to the mean lifetimes has been conducted. Continuing the previous study, a color map of the average output of the PELT+DARCSOULS algorithms is shown in figure 4b. We consider the group $\{P_0\}$ of N_0 pixels that were incorrectly characterized after applying the PELT method and the group $\{P_1\}$ of N_1 pixels from $\{P_0\}$ which are correctly characterized after applying DARCSOULS algorithm. The recovery rate is: $RR=N_1/N_0$. In this study, it is equal to 62%. The remaining 38% are: pixels with too low jump amplitude-to-white noise ratio, thus creating non detections (19%), or pixels with too low jump amplitude-to-drift amplitude ratio, thus preventing the correct separation of drift and RTS and increasing the characterization output error (19%). For the Gaussian method, the detection rate of “well behaved two level RTS pixels” after applying DARCSOULS is increased to 81% (6% increase).

In most of cases, applying AARD and DARCSOULS is enough to extract low error RTS amplitudes lifetimes and frequencies. In conclusion, these algorithms have enabled an automatic detection and characterization of the blinking pixels for the experimental study of the influence of the bias voltage on RTS signals.

INFLUENCE OF THE BIAS VOLTAGE ON THE RTS PIXELS NUMBER AND ACTIVATION ENERGY OF THE AMPLITUDE

The experimental FPA consists in a MWIR 15 μ m pitch n-on-p HgCdTe detector. Its cut-off wavelength at 80K is $\lambda_c=5.3\mu$ m. The detector is placed inside a continuous flow nitrogen cryostat, with an integrated heating system, enabling the control of the temperature with a precision of 30mK peak-to-peak. The detector is placed in front of an extended blackbody at $T_{BB}=298$ K with an optical aperture of f/8. Data cubes of 8000 images are

acquired with an integration time of 15ms, which also represents the interval between two images, as the detector is used in Integrate While Reading mode. The detector temperature varies between 110K and 122K, with a 3K step, and the bias voltage varies between V_0 and $V_0+0.3V$, with a 0.06V step and V_0 being the nominal reverse bias value. For this study, both types of protocol were explored: fixed reverse bias with varying temperature, and fixed temperature with varying reverse bias. As a summary, each experiment consists of 30 measurements, with a total observation time of 72 minutes, corresponding to $2.9 \cdot 10^5$ images to process.

First, the data cubes are processed through the AARD algorithm that allows the estimation of the number of RTS pixels of the FPA. In figure 6, the evolution of the number of RTS pixels in the detector as a function of the temperature and bias voltage is presented. In figure 6a), it is shown as a function of the bias voltage with different temperatures, and in figure 6b), it is shown as a function of the temperature with different bias voltage. In the former, it is clear that the increase in bias voltage increases the number of RTS pixels, but a fitting physical model has yet to be determined. It is yet clear that the rate of increase in function of the bias decreases with increasing temperature. A saturation effect may be considered. In figure 6b), it is possible to fit the different curves with an Arrhenius law, defined as follows:

$$X = X_0 e^{-\frac{E_a}{k_B T}} \quad (4)$$

With X a physical quantity ($X=N$ in the case of the number of RTS and $X=A$ in the case of the amplitude), X_0 a factor homogenous to X (which can depend on V_{bias}), E_a an activation energy, k_B the Boltzmann constant, and T the temperature of the detector. The fit shows that the number of RTS follows a Boltzmann law whichever the bias voltage is. The extracted activation energy is decreasing with increasing bias voltage; however, this is not directly interpretable, as the number of RTS detected is strongly dependent on different parameters, such as detection thresholds and RTS state definitions.

In a second study, the acquired data cubes are processed through the AARD and DARCSOULS algorithm in order to extract the evolution of the amplitude with the temperature and the bias voltage. Pixels that show too low amplitude to white noise ratio, display incorrigible drift or are simply false detections are manually removed, as the amplitudes cannot be estimated correctly in these cases. As an example, for two pixels, the amplitude as a function of the inverse of temperature is presented in figure 7 for different bias voltage. It shows that the amplitude increases with the bias voltage. In addition, whatever the voltage, the RTS amplitude follows an Arrhenius law, from which an activation energy can be extracted. These results are coherent with previous works [6].

The plot of the evolution of the Arrhenius activation energy as a function of bias voltage, for all the RTS pixels detected and studied is shown in figure 8. As shown on the graph, each pixel behaves differently and it would not be appropriate to study the RTS amplitude on the whole group of pixels. Two behaviors have been observed: pixels with decreasing activation energy as a function of bias, and pixels with constant activation energy as a function of bias. While keeping in mind that the amplitude increases with bias voltage for most of the pixels studied and the Arrhenius law defined in Equation (4), we can deduce that the pre-exponential factor of amplitude A_0 is also a contributor of the evolution of the amplitude. A_0 is a function of the reverse bias. The evolution of the amplitude as a function of bias is a non-trivial combination of the evolution of the factor A_0 and the evolution of the activation energy E_a contributions. We can hypothesize that high variations of the activation energy are due to the thermodynamic barrier associated with the jump being reduced along the increase in applied bias. It has already been shown that RTS was related to defects in the material [12]. A Poole-Frenkel [13] model could be considered, in which a dissymmetry of the band diagram around the defect implied in the process appears while applying a voltage to the system, thus lowering the barrier. In the case of low variation of activation energy, the results could go in favor of the Kinch model [14], with an enhancement of tunneling by the increase of the reverse bias. Also, according to this model, this could be due to the extension of the depletion region, caused by the reverse bias increase, in other words an extension of the cross-section that the diode depletion region presents to defects at the origin of RTS.

CONCLUSION

An RTS detection and characterization algorithm as well as a RTS and slow drift separation algorithm have been presented. They have then been used to characterize the evolution of the number of blinking pixels and blinking amplitudes as a function of temperature and bias voltage. It has been confirmed that the blinking process is characterized by an activation energy whichever bias voltage is applied, for the number of RTS pixels and the amplitudes of blinking. The RTS number and the amplitude increase with the bias voltage. The amplitude activation energy either decreases or stays constant with increasing reverse bias voltage. Physical models for either the evolution of the number of RTS with bias or the evolution of the amplitude with bias have yet to be developed. This study will be extended the blinking lifetimes and frequencies with PELT and LFNS methods in order to obtain a better understanding of the physics behind the RTS phenomenon in HgCdTe and bias effects.

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195 **CONFLICT OF INTEREST**

196 The authors declare that they have no conflict of interest.

197 **REFERENCES**

198 [1] Y. Kutovyi, I. Zadorozhnyi, N. Naumova, N. Boichuk, and M. Petrychuk in 25th International Conference on
199 Noise and Fluctuations (ICNF 2019) (2019).

200 [2] S.T. Hsu, Solid State Electron. 14, 487(1971).

201 [3] V. Goiffon, G.R. Hopkinson, P. Magnan, F.Bernard, G. Rolland, O. Saint-Pé, IEEE T. Nucl. Sci. 56, 4
202 (2009).

203 [4] I. Ribet-Mohamed, J. Nghiem, M. Caes, M. Guénin, L. Höglund, E. Costard, J.B. Rodriguez and P. Christol,
204 Infrared. Phys. Techn., 96, 145 (2019).

205 [5] D. Pogany, G. Guillot, Microelectron Reliab. 39, 341 (1999).

206 [6] A. Brunner, L. Rubaldo, V. Destefanis, F. Chabuel, A. Kerlain, D. Bauza and N. Baier, J. Electron. Mater.
207 43, 8 (2014).

208 [7] R. Kohley, R. Barbier, J.-C. Clémens, L. Conversi, P.-E. Crouzet, A. Ealet, S. Ferriol, W. Gillard, B. Kubik,
209 C. Rosset, A. Secroun, B. Serra, P. Strada, Proc. SPIE 10709, High Energy, Optical, and Infrared Detectors for
210 Astronomy VIII, 107091G (2018)

211 [8] R. Killick, P. Fearnhead and I.A. Eckley, J. Am. Stat. Assoc. 107,500,1590-1598 (2012).

212 [9] M. Guénin, S. Derelle, M. Caes, L. Rubaldo and I. Ribet-Mohamed in 25th International Conference on
213 Noise and Fluctuations (ICNF 2019) (2019).

214 [10] B.K. Jones, IEEE Trans. Electron. 41, 11 (1994).

215 [11] Y. Yuzhelevski, M. Yuzhelevski and G. Jung, Rev. Sci. Instrum, 71, 1681 (2000).

216 [12] P. Guinedor, A. Brunner, L. Rubaldo, D. Bauza, G. Reimbold and D. Billon-Lanfrey, J. Electron. Mater. 48,
217 6113 (2019).

218 [13] J. Frenkel, Phys. Rev. 54, 647 (1938).

219 [14] M.A. Kinch, C.-F. Wan, H. Schaake, and D. Chandra, Appl. Phys. Lett. 94, 193508 (2009)

220 **FIGURES CAPTIONS**

221 Figure 1: Typical behavior of a bi-stable RTS pixel. The straight line represents the signal. Dashed lines
222 represent the levels mean value.

223 Figure 2: Schematic principle of the Algorithm for Advanced RTS Detection, with the PELT algorithm, State
224 Reduction(SR) algorithm, LFNS method and Gaussian method.

225 Figure 3: Effect of the drift on the signal (left) and on the associated histograms (right)

226 Figure 4: Qualitative color map of the output of a) the PELT algorithm, b) the PELT+DARCSOULS algorithms.
227 A green cell corresponds to a major CD output; a red, vertically hashed one to a ND output; a blue, diagonally
228 hashed one to a CND output and an orange, horizontally hashed one to a FD output. Crossed cells represent
229 pixels detected due to the drift. Circles represent a strong error in the estimation of the RTS parameters.

230 Figure 5: a) Schematic principle of the RTS – drift separation algorithm b) Upper blue curve: RTS + drift
231 simulated signal. In red: local PELT estimation. Lower blue curve: signal with RTS compensation, equivalent to
232 slow drift with white noise. Green straight line: low pass filter of the lower blue curve, which is the estimated
233 slow drift. c) RTS signal extracted from b) by subtracting the low frequency signal from the original signal. In
234 orange binary signal is the final PELT estimation of the RTS in the pixel.

235 Figure 6: a) Normalized number of RTS pixels in the FPA as a function of bias voltage for different
236 temperatures. ΔV is the interval between the true bias and a reference bias V_0 , such as $V_{\text{bias}} = V_0 + \Delta V$. b)
237 Normalized number of RTS pixels in the FPA as a function of temperature for different bias voltages. Dashed
238 lines are respective Arrhenius fits for each bias.

239 Figure 7: RTS amplitude as a function of $1/T$ and the Arrhenius plots for several bias voltages of two different
240 pixels of the FPA.

Figure 8 Evolution of the activation energy for amplitude as a function of the reverse bias voltage for all the studied RTS pixels for low variation pixels (a)) and high variation pixels (b)). Each curve is a different pixel.

FIGURES

Figure 1: Guénin et al.

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Figure 5: Guénin et al.

Figure 6: Guénin et al.

Figure 7: Guénin et al.

Figure 8: Guénin et al.