Evaluation and monitoring of free running oscillators serving as source of randomness

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Introduction

Jittery clock - commonly used source of randomness in digital devices

- Clock jitter caused by several noise sources
 - White noise (thermal noise, ...)
 - $\,\hookrightarrow\,$ Best source of randomness, non manipulable
 - Autocorrelated noise (low frequency noises, e.g. flicker noise)
 - \hookrightarrow Entropy rate (unpredictability measure) difficult to quantify
 - Data dependent noise
 - \hookrightarrow Dangerous (manipulable), must be avoided

Jitter monitoring

- Continuous embedded monitoring is preferable
- Jitter usually quantified using the variance

$$\operatorname{var}(X) = \mathbb{E}(X^2) - [\mathbb{E}(X)]^2$$

Introduction





Randomness extraction methods from jittery clocks



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Free running oscillators as sources of randomness

Introduction

Objectives

- Analyze the use of variance for entropy estimation
- Use high order Markov model to estimate entropy coming from auto-correlated noises
- Compare performance of ROs and STRs as sources of randomness

Variance and Allan variance

- 2 High order Markov model for entropy rate estimation from autocorrelated signals
- 3 Experimental results

Characterization of random fluctuations of the clock frequency

Power spectral density (PSD)

• Defined as:

$$S_{y}(f) = h_{\alpha}f^{\alpha} \qquad (2$$

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- ▶ y dimensionless fractional frequency $(y = (\nu \nu_0)/\nu_0)$
- α constant characterizing the noise process
- h_α intensity of this noise
- Characterizes random fluctuations of the clock frequency

α	Type of the noise process
-2	Random Walk Frequency (RWF)
-1	Flicker Noise Frequency (FF)
0	White Noise Frequency (WF) or Random Walk Phase (RWP)
1	Flicker Noise Phase (FP)
2	White Noise Phase (WP)

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Variance of the frequency fluctuations

Main assumption

- y is an infinite zero-mean stationary process
 - \blacktriangleright characterized by its variance computed from a window of length τ

Variance can be computed using the power spectral density

- Corollary of the Wiener-Khinchin theorem
- Variance of y computed from the power spectral density $S_y(f)$:

$$\sigma_y^2(\tau) = \int_0^{+\infty} S_y(f) \times |H_\tau(f)|^2 df, \qquad (3)$$

whenever it exists.

- $H_{\tau}(f)$ is the transfer function of the variance operator:

 - $\,\hookrightarrow\,$ Depends on the type of variance computed

Computation of the statistical variance from the PSD



Frequency domain
$$|H_{\tau}(f)|^2 = \left(\frac{\sin(\pi \tau f)}{\pi \tau f}\right)^2 \quad (4)$$

Variance of the jitter computed for $\alpha \in [-2; 2]$ from time window τ

$$\sigma_y^2(\tau) = \sum_{\alpha=-2}^2 \frac{h_{\alpha}}{(\pi\tau)^2} \int_0^{f_h} f^{\alpha-2} \sin^2(\pi\tau f) df.$$
 (5)

Problem: if α ≤ −1, the integral does not converge as f tends to 0
The use of the statistical variance can cause entropy overestimation

Allan variance and its computation from the PSD



Frequency domain

$$|H_{\tau}(f)|^2 = \left(\frac{\sin(\pi\tau f)}{\pi\tau f}\right)^2 \sin^2(\pi\tau f) \quad (6)$$

Allan Variance of the jitter computed for $\alpha \in [-2; 2]$ from window au

$$\sigma_y^2(au) = \sum_{lpha=-2}^2 rac{2h_lpha}{(\pi au)^2} \int_0^{f_h} f^{lpha-2} \sin^4(\pi au f) df$$

• Convergence ensured for $\alpha > -3$ as f tends to 0:

Allan variance is accurate, even in presence of low frequency noises

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(7)

Allan variance estimation from a limited data set

An average fractional frequency can be used

- Average frequency deviation \overline{y}_k over a time interval of length τ
 - \blacktriangleright Corresponds to the fluctuations while counting the number of periods of the jittery signal over τ
- Estimate of the Allan variance:

$$\sigma_{y}^{2}(\tau) = \frac{1}{2(M-1)} \sum_{i=1}^{M-1} \left(\overline{y}_{i+1} - \overline{y}_{i} \right)^{2}.$$
 (8)

 \hookrightarrow *M* : total number of \overline{y}_k 's.

 For α = 0, σ²_y(τ) is an unbiased estimator of the variance even for a finite M

High order Markov model for entropy rate estimation Experimental results

Experimental results



- Variance dependence on the number of samples *M*
 - Allan variance stable
 - Statistical variance increases with M



- Variance dependence on the jitter accumulcation period k
 - Allan variance always below statistical variance
 - Statistical variance causes entropy rate overestimation

• Similar results for both types of free running oscillators studied

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High order Markov model for entropy rate estimation Experimental results

Hardware implementations

• Statistical variance



3 adders/subtractors, 2 multipliers

Allan variance



1 adder/subtractor, 1 multiplier

Comparison with the state-of-the-art methods

Method	Area		f _{max}	Power
	ALM/Regs	DSPs	[MHz]	[mW]
Haddad <i>et al.</i>	119/160	2	178.3	6-7
Fischer and Lubicz	169/200	4	187.7	7-8
Proposed method, Eq. (8)	49/117	1	238.5	4-5

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- High order Markov model for entropy rate estimation from autocorrelated signals
- 3 Experimental results

The use of high order Markov chain models for entropy estimation 14

Min-entropy

- Min-entropy is the most conservative entropy measure
 - Avoids entropy rate overestimation
 - Hard to estimate in general
- Recent approach offers efficient way to estimate min-entropy^a:
 - Information sources modeled as high order Markov chains

Markov chain

- Convenient to model temporal short-term dependencies
 - Higher order models give more accuracy but are much more complex
- Depending on jitter properties and the randomness extraction process, we use an 8-th order Markov model to study dependencies
 - \blacktriangleright Model parameters: $\{0,1\}^8$ states, transition matrix $2^8\times 2^8$

^aS. Kamath and S. Verdu, Estimation of entropy rate and Renyi entropy rate for Markov chains, IEEE International Symposium on Information Theory 2016

Entropy estimates from the 8-th order Markov chain model

Randomness extraction method: sampling the jittery clock

Jitter accumulation time	Markov	AIS 31	AIS 31 T8	NIST	NIST
	chain	Procedure B		800-90B	800-90B
Periods of s_2	min-entropy		Shannon entropy	IID	min-entropy
10 000	0.8102	failed	0.9844	non-IID	0.648
20 000	0.8105	failed	0.9851	non-IID	0.647
30 000	0.8102	failed	0.9847	non-IID	0.648
50 000	0.9369	failed	0.9992	non-IID	0.673
100 000	0.9012	failed	0.9935	non-IID	0.670

Randomness extraction method: counting the jittery clock periods

Jitter accumulation time	Markov chain	AIS 31	AIS 31 T8	NIST	NIST
		Procedure B		800-90B	800-90B
Periods of s ₂	min-entropy		Shannon entropy	IID	min-entropy
10 000	0.8089	failed	0.9966	non-IID	0.844
15 000	0.9769	passed	0.9998	non-IID	0.931
20 000	0.9865	passed	0.9999	IID	0.999
25 000	0.9907	passed	0.9999	IID	0.998
100 000	0.9910	passed	0.9999	IID	0.998

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Impact of the surrounding logic on the jitter and entropy rate

- Three projects implemented
- Blocks placed exactly on the same place in the same FPGA



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Impact of the surrounding logic on the jitter and entropy rate

Project	$\sigma_1 \; [ps]$	$\sigma_2 \text{ [ps]}$	Var(cnt)	Avar(N)
Project 1 (just two rings)	3.9	3.3	14.01	2.79
Project 2 (ring + ext.osc. + other logic)	9.7	7.3	26.94	4.33
Project 3 (two rings $+$ other logic)	10.6	10.0	14.72	2.76

- Oscillator jitter increases when a full cryptosystem is implemented
 - Surrounding logic has inevitable impact on clock jitters
- However, variances of counter values do not change when both oscillators are implemented inside the device!
- External clocks
 - Cause entropy rate overestimation
 - Introduce manipulable global noise sources into the generator

Comparison of RO and STR as sources of randomness

- Autocorrelation of raw counter values and their first differences
 - Two identical rings (RO or STR)
 - One ring (RO or STR) and an external quartz oscillator



- RO and STR exhibit the same behavior in terms of jitter produced
- The use of identical oscillators reduces autocorrelations
- First order difference removes large portion of autocorrelation

Conclusions

- Counting jittery clock periods gives higher quality random numbers
 - Higher bit rate with higher entropy rate
 - Counter values can be used for online jitter monitoring
- Allan variance should be used to estimate entropy rate rather than the statistical variance
 - Not sensitive to window size impact of low frequency noises can be reduced using small windows without loosing precision
 - Smaller circuitry required for implementation
- Differential principle of the TRNG design is a stringent requirement, not a recommendation
 - Global, manipulable noises are strong and always present
- High order Markov chain models provide good min-entropy estimates and are efficient to detect dependencies in generated numbers

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Hardware Enabled Crypto and Randomness

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