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Statistical Simulation for BIST Architecture using Cognitive Principles

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Abstract: ***In this paper, we have used the concept of cognitive radio networks to estimate optimum error probability for the estimation of failure rate inBIST (built in self test) architecture. In this work primarily the problem of BIST has been dealt from the point of view of probability theorem especially central limit theorem and chi square distribution. Earlier this work has been used to estimate the probability distribution for cognitive radio technology. Now our effort underlies its use in BIST analysis. In BIST architecture usually we face a tradeoff in between no. of gates used in the BIST, the probability of false alarm i.e. whether the read write generated is true or not, probability of detection which shows that whether the particular memory prone has been successfully tested. Thus this project work focuses on the use of cognitive radio principles for estimation of read/write error in testing any type of memory. The project work will result in the finding of a tradeoff between optimum probability of false alarm and probability of detection for a general BIST in consideration.***

Keywords: BIST , VLSI , statistical analysis , cognitive radios , montecarlo simulation

1. Introduction to Cognitive Principles

The long term vision of cognitive radio technology is one in which handsets would automatically make use of underutilized spectrum across a broad frequency range, allowing the high bandwidth requirements of the future. If a radio were smart, it could learn services available in locally accessible wireless computer networks, and could interact with those networks in their preferred protocols, to have no confusion in finding the right wireless network for a video download or a printout. Additionally, it could use the frequencies and choose waveforms that minimize and avoid interference with existing radio communication systems. It might be like having a friend in everything that's important to your daily life. The sophistication possible in a software-defined radio (SDR) has now reached the level where each radio can conceivably perform beneficial tasks that help the user, help the network, and help minimize spectral congestion.

The development of digital signal processing (DSP) techniques arose due to the efforts of such leaders as Alan Oppenheim, Lawrence Rabiner, Ronald Schaefer, Ben Gold, Thomas Parks, James McClellen, James Flanagan, Fred Harris, and James Kaiser. These pioneers recognized the potential for digital filtering and DSP, and prepared the seminal textbooks, innovative papers, and breakthrough signal processing techniques to teach an entire industry how to convert analog signal processes to digital processes.

Meanwhile, the semiconductor industry, continuing to follow Moore's law, evolved to the point where analog functions implemented with large discrete components were replaced with digital functions implemented in silicon, and consequently were more producible, less expensive, more reliable, smaller, and of lower power. During this same period, researchers all over the globe explored various techniques to achieve machine learning and related methods for improved machine behavior. Among these were analog threshold logic, which lead to fuzzy logic and neural networks, a field founded by Frank Rosenblatt. In networking, DARPA and industrial developers at Xerox, BBN Technologies, IBM, ATT, and Cisco each developed computer-networking techniques, which evolved into the standard Ethernet and Internet we all benefit from today. The researchers are exploring wireless networks that range from access directly via a radio access point to more advanced techniques in which intermediate radio nodes serve as repeaters to forward data packets toward their eventual destination in an ad hoc network topology. Cognitive radios are nearly always applications that sit on top of an SDR, which in turn is implemented largely from digital signal processors and general-purpose processors (GPPs) built in silicon.

2. BIST & Various Approaches

With increasing design complexity in modern SOC design, many memory instances with different sizes and types would be included. To test all of the memory with relatively low cost becomes an important issue. Providing user-defined pattern for screening out various manufacturing defects is also a major demand. To ease the trade-off between the hardware cost and test flexibility, Programmable Built-In Self-Test (P-MBIST) method is an opening approach to complete the memory testing under these circumstances. Many researchers have been focused on P-MBIST design. Processor-based architecture provides high test flexibility, but it increases the test development costs while applying to various processor families. To lower the design cost, a customized processor and instruction have been developed. It uses program memory to store the test program. To further reduce the hardware cost, the instruction can be serially input and saved in one internal register by adopting simple controller. With the advent of deep-submicron VLSI technology, core-based system-on-chip (SOC) design is attracting an increasing attention. On an SOC, popular reusable cores include memories (such as ROM, SRAM, DRAM and flash memory), processors (such as CPU, DSP and microcontroller), input/output circuits, etc. Memory cores are obviously among the most universal ones-almost all system chips contain some type of embedded memory.

However, to provide a low cost-cost test solution for the on-chip memory cores is not a trivial task. This paper shall serve as a knowledge base for future design in memory BIST.

Spectrum Sensing Basic Theory

In this section, we first present the general model for spectrum sensing, then review the energy detection scheme and analyze the relationship between the probability of detection and the probability of false alarm.

3. General Model for Spectrum Sensing

Suppose that we are interested in the frequency band with carrier frequency fc and bandwidth W and the received signal is sampled at sampling frequency fs. When the primary user is active, the discrete received signal at the secondary user can be represented as :

$$y(n) = s(n) + u(n),$$

which i s t he output under hypothesis H1 . When the primary user is inactive, the received signal is given by

and this case i s referred to as hypothesis H0 .We make the following assumptions.

- (AS1) The noise u(n) is a Gaussian, independent and identically distributed (iiid) r andom process with mean zero and variance E[|u(n)|2]= σ2 u;
- (AS2) The primary signal s(n) is an iid random process with mean zero and variance E[|s(n)|2]= σ2s ;
- (AS3) The primary signal s(n) is independent of the noise u(n).

Two probabilities are of interest for spectrum sensing: probability of detection, which defines, under hypothesis H1, the probability of the algorithm correctly detecting the presence of primary signal; and probability of false alarm, which defines, under hypothesis H0, the probability of the algorithm falsely declaring the presence of primary signal. From the primary user's perspective, the higher the probability of detection, the better protection it receives. From the secondary user's perspective, however, the lower the probability of false alarm, there are more chances for which the secondary users can use the frequency bands when they are available. Obviously, for a good detection algorithm, the probability of detection should be as high as possible while the probability of false alarm should be as low as possible. We focus on the complex-valued PSK signal and CSCG noise case. Based on the PDF of the test static, the probability of detection can be approximated by

For a target probability of detection, Pf can be calculated from Pd or vice versa as shown in the above equation, this equation serves for us as the basic equation for our project.

4. Monte Carlo Simulation Basics

Monte Carlo methods (or Monte Carlo experiments) are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results; typically one runs simulations many times over in order to obtain the distribution of an unknown probabilistic entity. The name comes from the resemblance of the technique to the act of playing and recording your results in a real gambling casino. They are often used in physical and mathematical problems and are most useful when it is difficult or impossible to obtain a closed-form expression, or infeasible to apply a deterministic algorithm. Monte Carlo methods are mainly used in three distinct problem classes: optimization, numerical integration and generation of draws from a probability distribution.

In physics-related problems, Monte Carlo methods are quite useful for simulating systems with many coupled degrees of freedom, such as fluids, disordered materials, strongly coupled solids, and cellular structures (see cellular Potts model). Other examples include modeling phenomena with significant uncertainty in inputs, such as the calculation of risk in business; and, in math, evaluation of multidimensional definite integrals with complicated boundary conditions. In application to space and oil exploration problems, Monte Carlo–based predictions of failure, cost overruns and schedule overruns are routinely better than human intuition or alternative "soft" methods. The modern version of the Monte Carlo method was invented in the late 1940s by StanislawUlam, while he was working on nuclear weapons projects at the Los Alamos National Laboratory. It was named by Nicholas Metropolis, after the Monte Carlo Casino, where Ulam's uncle often gambled. Immediately after Ulam's breakthrough, John von Neumann understood its importance and programmed the ENIAC computer to carry out Monte Carlo calculations. Monte Carlo methods vary, but tend to follow a particular pattern:

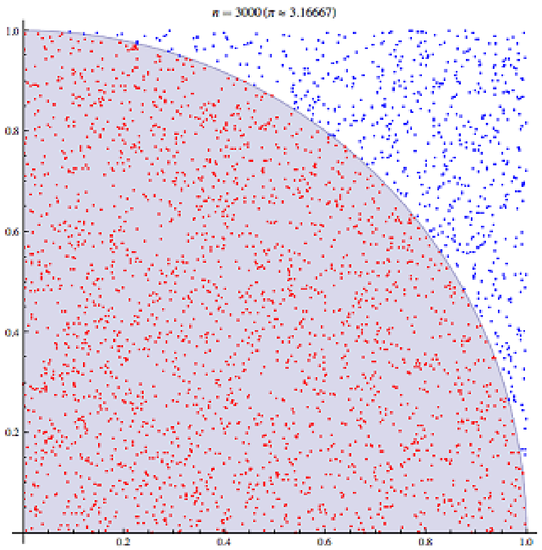
1) Define a domain of possible inputs.
2) Generate inputs randomly from a probability distribution over the domain.
3) Perform a deterministic computation on the inputs.
4) Aggregate the results.

For example, consider a circle inscribed in a unit square. Given that the circle and the square have a ratio of areas that is π/4, the value of π can be approximated using a Monte Carlo method:

a. Draw a square on the ground, then inscribe a circle within it.
b. Uniformly scatter some objects of uniform size (grains of rice or sand) over the square.
c. Count the number of objects inside the circle and the total number of objects.

4.4. The ratio of the two counts is an estimate of the ratio of the two areas, which is π/4. Multiply the result by 4 to estimate π.
In this procedure the domain of inputs is the square that circumscribes our circle. We generate random inputs by scattering grains over the square then perform a computation on each input (test whether it falls within the circle). Finally, we aggregate the results to obtain our final result, the approximation of π. If the grains are not uniformly distributed, then our approximation will be poor. Secondly, there should be a large number of inputs. The approximation is generally poor if only a few grains are randomly dropped

into the whole square. On average, the approximation improves as more grains are dropped.



Monte Carlo method applied to approximating the value of π. After placing 30000 random points, the estimate for π is within 0.07% of the actual value. This happens with an approximate probability of 20%.

Figure 1: Highlighting Monte Carlo Method basic design

5. Simulation Results

A graphical user interface has been created in Matlab for realizing the above concepts , in the GUI the user can select the no of gates , i.e the density of memory to be reviewed , also the user can chose the type of noise (in our case the irregularness of the implemented algorithm) with which the memory is tested in addition to this the user can also select the no of iteration for montecarlo simulation , the fig 2 shown below shows the said GUI :-

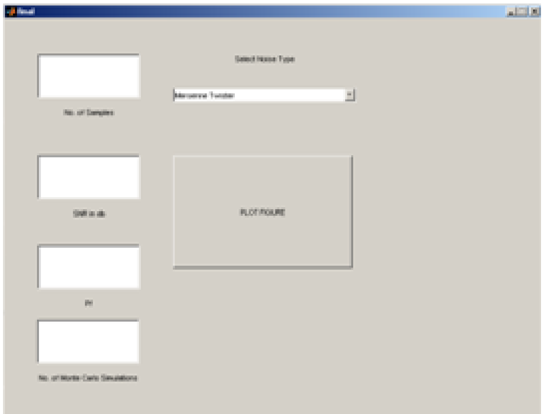


Figure 2: GUI Built in Matlab

Several combinations are now available to analyze the application of cognitive radio principles to BIST architecture, examples of some are as given below :-

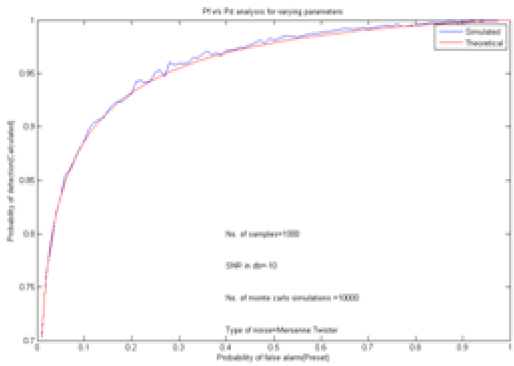


Figure 3: One of the several results

With the help of such an analysis we are able to find which particular settings exactly come close to theoretical and simulation values , for our project the values of parameters are as under :-
1) No. of samples = 1000
2) SNR =-10db
3) Pf range= 0:0.01:1
4) No. of Monte Carlo simulations = 10000
5) Noise type = Random generator with normal distribution (AWGN type)

Far better results can be obtained if we could increase the montecarlo simulation but due to constraints on computational resources it is not always possible.

6. Conclusions

Our is perhaps one of the first attempts to generalize the BIST architecture problem and model the complete deterministic problem (as typically is the case with all VKLSI problems) into a statistical one , but the use of statistical mathematics in analysis of communication system have shown us that indeed the approach has been successful . We wish that the research community will acknowledge the work ands will take the work from here on to new heights.

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