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APPLYING CHI SQUARED DISTRIBUTION AND CENTRAL LIMITING THEOREM TO ESTIMATE THE OPTIMUM PLACEMENT DENSITY IN ASIC

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ABSTRACT

In today's world when chip size is getting more and more compact using different partitioning iterative and better floor planning, enabling us to make a design i.e. ASIC more useful and multitasking, there is wide space for further development of techniques in this area. This issue can be significantly addressed by NANO Technology. And as current scenario deal with VLSI so making some efficient iterative in conventional designing can bring a major change in field of ASIC size and density, which is although the main concern of design process.

Keywords: *CLT, FPGA, ASIC, Placement, Partitioning, Routing.*

1. INTRODUCTION

In this project, we have used the concept of cognitive radio networks to estimate optimum placement density used in ASIC placement. In this work primarily the problem of ASIC placement 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 ASIC placement. In ASIC placement usually we face a tradeoff in between no. of gates used in the ASIC, the probability of false alarm i.e. whether the gate placement will lead to error or not, probability of detection which shows that whether the placement is better than the previous one or not. Thus this project work focuses on the use of cognitive radio principles for estimation of optimum ASIC placement. The project work will result in the finding of a tradeoff between optimum probability of false alarm and probability of detection for a particular ASIC in consideration.

1.1 APPLICATION SPECIFIC INTEGRATED CIRCUIT

A digital application-specific integrated circuits (ASICs) consist of rows of logic gates connected by wires. The connecting wires are located between logic gate rows in specific routing channels. ASICs are commonly used for a full-custom design, where the circuit is created for a specific purpose and can be designed in a more detailed manner.

Various kinds of logic gates can be used in the ASIC. They are pre-designed and collected in a library available to the designer. Standard cells are commonly used in situations where the designer does not need complete flexibility for the layout of each individual transistor, as part of the design effort can be avoided by using standard cells.

1.2 BASIC TECHNIQUES

Currently, placement is usually separated into global and detailed placement. State of the art global placement algorithms include analytical techniques, which approximate the wire-length objective using quadratic or nonlinear formulations, and min-cut placers which use graph partitioning algorithms.

Detailed placement uses various kinds of local optimizations, including simulated annealing. Simulated annealing has also been used for the complete placement flow since its proposal as a general combinatorial optimization technique before being replaced by analytical and min-cut placers.

In some approaches the floorplan may be a partition of the whole chip area into axis aligned rectangles to be occupied by IC blocks. This partition is subject to various constraints and requirements of optimization:

Block area, aspect ratios, estimated total measure of interconnects, etc.

Finding good floorplans has been a research area in combinatorial optimization. Most of the problems related to finding optimal floorplans are NP-hard, i.e., requiring vast computational resources. Therefore, the most common approach is to use various optimization heuristics for finding good solutions.

Another approach is to restrict design methodology to certain classes of floorplans, such as sliceable floorplans.

2. PLACEMENT SENSING PRELIMINARIES

In this section, we first present the general model for placement sensing, then review the placement detection scheme and analyze the relationship between the

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probability of detection and the probability of false alarm.

General Model for Placement Sensing

Suppose that we are interested in the n number of gates and working block size f_c and total block size W maximum number of gates can be used f_s. When the primary user is active, the received signal at the secondary user can be represented as:

$$y(n) = s(n) + u(n) \quad (1)$$

Which is the output under hypothesis H_1? When the primary user is inactive, the received signal is given by:

$$y(n) = u(n) \quad (2)$$

And this case is referred to as hypothesis H_0. We make the following assumptions.

(AS1) The error $u(n)$ is a Gaussian, independent and identically distributed (iiid) random process with mean zero and variance $E[|u(n)|^2 = \sigma_u^2]$; (AS2) The primary signal $s(n)$ is an iid random process with mean zero and variance $E[|s(n)|^2] = \sigma_s^2$;(AS3) The primary signal $s(n)$ is independent of the error $u(n)$.

Denote $\gamma = \frac{\sigma_s^2}{\sigma_u^2}$ as the received detection to error ratio (SNR) of the primary user measured at the secondary receiver of interest, under the hypothesis H_1. We consider both real valued Gaussian error case and circularly symmetric complex Gaussian (CSCG) error case. For the primary signal $s(n)$, we consider two scenarios: (1) real-valued Gaussian signal; (2) CSCG signal.

Two probabilities are of interest for placement sensing: probability of detection, which defines, under hypothesis H_1, the probability of the algorithm correctly detecting the presence of primary signal; and probability of false alarm, which defines, under hypothesis H_0, 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.

2.1 PROBALISTIC APPROACH

Let τ be the available sensing time and N the number of samples (N is the maximum integer not greater than τf_s, and for notation simplicity, we assume $N = \tau f_s$. The test statistic for energy detector is given by

$$T(y) = \frac{1}{N}\sum_{n=1}^{N}|y(n)|^2 \quad (3)$$

Under hypothesis $H0$, the test static $T(y)$ is a random variable whose probability density function (PDF) $p_0(x)$ is a Chi-square distribution with $2N$ degrees of freedom for complex valued case, and with N degrees of freedom for real-valued case. If we choose the detection threshold as ϵ, the probability of false alarm is then given by

$$P_f(\epsilon,\tau) = P_r(T(y) > \epsilon|\mathcal{H}_0)$$

$$= \int_{\epsilon}^{\infty} p_0(x)dx \quad (4)$$

Using central limit theorem (CLT), we have the following proposition.

Proposition 1: For a large N, the PDF of $T(y)$ under hypothesis H_0 can be approximated by a Gaussian distribution with mean $\mu_0 = \sigma_u^2$ and variance $\sigma_0^2 = \frac{1}{N}[E|u(n)|^4 - (\sigma_u)^2]$.

Further,

- If $u(n)$ is real-valued Gaussian variable, then $E|u(n)|^4 = 3\sigma_u^4$, thus $u\sigma_0^2 = \frac{1}{N}\sigma_u^4$.

- If $u(n)$ is CSCG, then $E|u(n)|^4 = 2\sigma_u^4$, thus $\sigma_0^2 = \frac{1}{N}\sigma_u^4$.

Next, we focus on the CSCG noise case for which the probability of false alarm is given by:

$$P_f(\epsilon,\tau) = \mathcal{Q}\left(\left(\frac{\epsilon}{\sigma_u^2} - 1\right)\sqrt{\tau f_s}\right) \quad (5)$$

Where Q(·) is the complementary distribution function of the standard Gaussian, i.e.,

$$\mathcal{Q}(\mathrm{x}) = \frac{1}{\sqrt{2\pi}}\int_{\mathrm{x}}^{\infty}\exp\left(\frac{-\mathrm{t}^2}{2}\right)\mathrm{dt} \quad (6)$$

Under hypothesis H_1, denote p1(x) as the PDF of the test static T(y). For a chosen threshold ϵ, the probability of detection is given by:

$$P_d(\epsilon,\tau) = P_r(T(y) > \epsilon|\mathcal{H}_1) = \int_{\epsilon}^{\infty} p_1(x)dx \quad (7)$$

Proposition 2: For a large N, the PDF of T(y) under hypothesis H_1 can be approximated by a Gaussian distribution with mean $\mu_1 = (\gamma + 1)\ \sigma_u^2$ and variance

$$\sigma_1^2 = \frac{1}{N}[E|s(n)|^4 + E|u(n)|^4 - (\sigma_s^2 - \sigma_u^2)^2] \quad (8)$$

if s(n) and u(n) are both circularly symmetric and complex valued, and

$$\sigma_1^2 = \frac{1}{N}[E|s(n)|^4 + E|u(n)|^4 - (\sigma_s^2 - \sigma_u^2)^2 + 2\sigma_s^2\sigma_u^2] \quad (9)$$

if s(n) and u(n) are both real-valued. Furthermore,

- If s(n) and u(n) are both CSCG, $E|s(n)|^4 = 2\sigma_s^4$ and $E|u(n)|^4 = 2\sigma_u^4$, then $\sigma_1^2 = \frac{1}{N}(\gamma + 1)^2\sigma_u^4$;

- If s(n) and u(n) are both real-valued Gaussian, $E|s(n)|^4 = 3\sigma_s^4$ and $E|u(n)|^4 = 3\sigma_u^4$, then $\sigma_1^2 = \frac{2}{N}(\gamma + 1)^2\sigma_u^4$;

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.Proof: The proof is again based on CLT.

Remark: For the two cases of primary user's signal and additive disturbance we considered, the complex counterpart yields half the variance as that of the real-valued case. This can be understood by considering the fact that the complex case, in fact, provides twice the samples as compared to the real-valued case.

We focus on the real-valued signal and CSCG disturbance case. Based on the PDF of the test static, the probability of detection can be approximated by

$$P_f(\epsilon,\tau) = \mathcal{Q}\left(\left(\frac{\epsilon}{\sigma_u^2} - 1 - \gamma\right)\sqrt{\frac{\tau f_s}{\sqrt{2\gamma+1}}}\right) \qquad (10)$$

For a target probability of detection $\overline{P}_d$, the detection threshold ϵ can be determined by

$$\left(\frac{\epsilon}{\sigma_1^2} - \gamma - 1\right)\sqrt{\frac{\tau f_s}{\sqrt{2\gamma+1}}} = \mathcal{Q}^{-1}(\overline{P}_d) \qquad (11)$$

From (5), on the other hand, this threshold is related to the probability of false alarm as follows:

$$\mathcal{Q}^{-1}(P_f) = \left(\frac{\epsilon}{\sigma_u^2} - 1\right)\sqrt{\tau f_s} \qquad (12)$$

Therefore, for a target probability of detection, $\overline{P}_d$, the probability of false alarm is related to the target detection probability as follows:

$$P_f = \mathcal{Q}\left(\sqrt{2\gamma+1}\,\mathcal{Q}^{-1}(\overline{P}_d) + \sqrt{\tau f_s}\,\gamma\right) \qquad (13)$$

On the other hand, for a target probability of false alarm $\overline{P}_f$, the probability of detection is given by

$$P_d = \mathcal{Q}\left(\frac{1}{\sqrt{2\gamma+1}}\left(\mathcal{Q}^{-1}(\overline{P}_f) + \sqrt{\tau f_s}\,\gamma\right)\right) \qquad (14)$$

Finally, for a given pair of target probabilities (P_d, P_f), the number of required samples to achieve these targets can be determined from (11) and (12) by cancelling out the threshold variable ϵ.

3. RESULTS

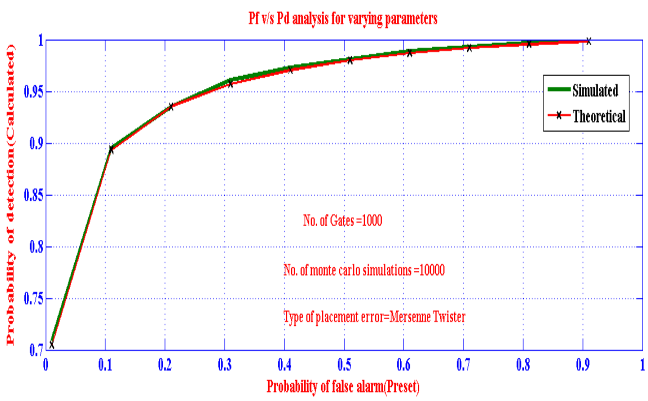

Fig. (a) Plot of P_d v/s P_f for Mersenne Twister Placement Error for Number of Gates =1000.

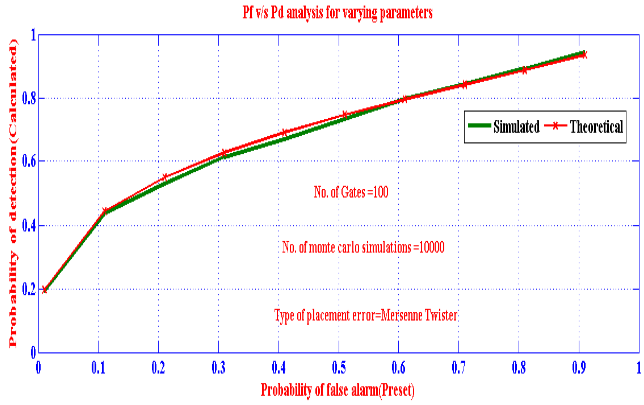

Fig. (b) Plot of P_d v/s P_f for Mersenne Twister Placement Error for Number of Gates =1000.

4. CONCLUSION

It has been clearly evident from the results that the theoretical and simulated results match for number of gates inn ASIC as 1000, number of montecarlo simulation as 10000 iteration and mersenne twister type placement error. Along with this every simulation evident that this work of applying chi square distribution and CLT to the placement in ASIC design gives more comprehensive outcomes when applied for larger number of gates or it can be modeled as larger number of ASIC components for the practical environment.

As shown in all the characteristics above we have compared each characteristic for two models of design, one is a design with number of gates to be placed or we can say number of components to be placed is 100 and in the next characteristic we have shown the same characteristic with only one change i.e. number of components or number of gates to be placed in an ASIC is increased to 1000. This change in number of components to be placed in ASIC make the theoretical and calculated characteristic more aligned to each other, and these characteristics get more aligned as the number of components to be placed in ASIC increases.

And from the result figures it can be stated that we can make a throughput tradeoff between the probability of false alarm and probability of true detection for the placement in the ASIC by using above work ,which is quiet correlated to the cognitive radio concept and is can be done almost with highest accuracy by applying Central Limiting Theorem and Chi Square Distribution model of probability .

5. FUTURE SCOPE

The circuit partitioning problem is a well known NP hard problem. Various traditional algorithms are used to solve his problem. But due to their complexity a better way is to use probabilistic approach. This report introduced the partition problem as well as the new technique to approach this problem using chi square distribution and central limiting theorem. An algorithm using montecarlo simulation techniques with local optimization was developed for solving the graph partitioning problem. The effectiveness of the technique is shown with experimental results.

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In future scope more factors could be added to the move selection that would force the colonies away from each other. This could make the algorithm even more competitive when compared with other heuristic algorithms.

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