

A Performance Driven Layout Compaction Optimization Algorithm for Analog Circuits

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Abstract – In interconnect-dominated designs, the ability to minimize layout-induced parasitic effects is crucial for rapid design closure. Deep sub-micron effects and ubiquitous interference in mixed-signal environments cause designers to be less reliant on optimization based solely on schematic models. Performance can be further improved at the physical design level. Hierarchical optimization schemes are used to manage the complexity in the analog circuit design process. In this paper, we present a novel performance-driven compaction optimization algorithm that optimizes the placement of circuit blocks and guard bands for analog circuits. Parasitic effects are minimized under symmetry, matching and displacement constraints derived from the customized layout topology.

I. INTRODUCTION

High demands of quality electronic devices have driven the interests in rapid design and development of robust mixed-signal integrated circuits using deep-submicron (DSM) technologies. A key concern for DSM design closure is the parasitic coupling through the interconnect, packaging and substrate parasitics, due to non-ideal electrical isolations. Under the shortened design cycle times, efficient physical design techniques and accurate parasitic coupling models are needed in overcoming signal integrity issues, achieving the desired quality and productivity.

Due to the regenerative nature of digital signals, automated physical design generation tools have long been effective in synthesizing digital hardware subsystems. Meanwhile, analog components are still largely crafted from bottom-up. To keep pace with logic design, top-down design flow is urgently needed [1]. Unless with overly pessimistic specifications, robustness at the top abstraction level against interference such as substrate coupling and routing parasitics is *not* guaranteed until the detailed physical design information is extracted. To improve design closure, a hierarchical optimization scheme that continually refines design options throughout the top-down design flow is suggested (Fig. 1). In this paper, we propose a performance-driven, simulation based *compaction optimization* technique, where the designer supplies a physical design and its exact block and guard band locations are optimized. Based on the given layout topology for CMOS bulk substrate process, cost functions in terms of interconnect and substrate coupling parasitics are minimized while subjected to block symmetry, matching and displacement constraints. The algorithm explores possible reductions of performance impact due to layout effects with no change in existing schematic and physical design topology.

Placement is a critical step in the physical design flow to ensure satisfactory performance, because layout parasitics and routability are strongly dependent on quality physical placement. Placement algorithms can be separated into 2 major classes: partitioning-based and simulation-based algorithms. Partitioning algorithms divide the complex problem repeatedly into smaller, more manageable sub-problems. Within each level, the *geometric* partitioning is optimized with respect to objective functions, using a pre-determined partition style. Partitioning-based algorithms are more suitable for large circuits where global exploration of placement possibilities cannot be performed efficiently. In simulation-based algorithms, randomly or evolutionarily generated trial placements are carried out. Performance or resource related cost functions are

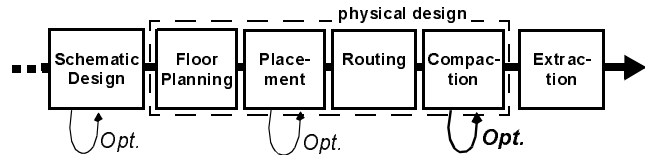


Fig. 1 Hierarchical optimization in physical design

used to compare the quality of the placements against each others. Several methods, such as Monte Carlo [2], simulated annealing [3] and simulated evolution [4] algorithms, determine the optimization trajectories in the placement space. Compared to partitioning-based algorithms, they are relatively more computationally intensive, but yield better solutions for small and medium sized circuits.

The primary objective of automated placement algorithms for digital VLSI circuits is to synthesize design rule-correct hardware from hardware description code, fitting all required blocks densely into the specified area, while minimizing the occupancy area and the lengths of interconnecting nets. In contrast, analog circuits are smaller and often benefit from additional separation area, dummy devices or insertion of guard bands [5]. To reduce detrimental effects due to parasitic coupling and fabrication process variations. Analog physical synthesis is a much more challenging problem due to additional layout constraints. It is difficult to identify the canonical analog design space as legitimate solutions satisfying all constraints only constitute a small portion of many possible permutations. To avoid run time inefficiency, analog physical synthesis is usually performed manually, or automated for specific circuit types, or by placement methodologies that only determine the relative packing configurations among circuit blocks.

Additional performance can be gained by fine-tuning their exact positions after placement and routing, as more parasitic details are revealed. This compliments analog designers and tools to improve the quality and performance of their customized physical designs, where their experience and knowledge excel. We propose a performance-driven *compaction* optimization technique through minimizing the layout parasitics of the given physical design topology. It also examines and improves potentially over-designed objects such as guard ring and guard band objects that were created traditionally without proper modeling. The algorithm is admissible for any given analog physical design, unrestricted by standard design templates.

II. PLACEMENT CONSTRAINTS

While a compact placement that minimizes separation distances and total area consumption is often advantageous to accommodate large gate-count digital circuits, analog circuits may benefit from some additional separation distances among devices for reducing interference. As parasitic resistances along interconnects increase for an overly slack placement, the optimum analog circuit compaction is somewhere in between, to be determined by the optimization algorithm.

2.1 Maximum Horizontal Strip Representation

The compaction optimizer accepts a preliminary physical placement with symmetry properties specified. For simplicity, devices core, including routing area, are represented by non-overlapped rectangular blocks so that they allow flushed packing with no space in between. Each block can specify *self* or *mirror symmetry*

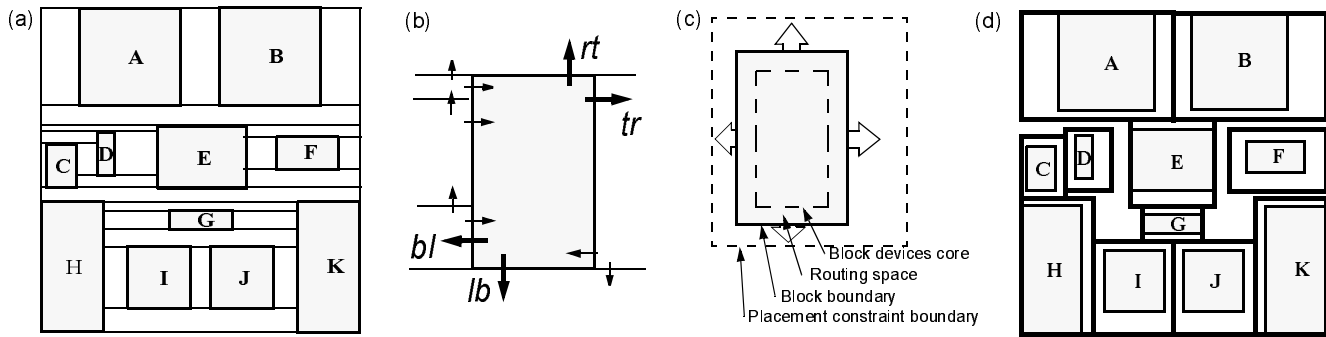


Fig. 2 (a) Placement of an analog design with self-symmetry blocks E, G and mirror symmetry block pairs $(A,B), (I,J), (H,K)$ along the central vertical axis (b) MHS partition of an analog placement (c) Block and placement constraints boundaries (d) Placement constraints derived from MHS partition

with another block and the corresponding symmetry axis in its property list. The *corner stitching* scheme [6], along with the *maximum horizontal strip* (MHS) partition are implemented to allow search and modification of block positions in linear time. Fig. 2(a) and (b) shows the MHS partition and the corner stitching scheme respectively. The MHS partition can simply be constructed by extending the horizontal boundaries of each block until they reach the boundaries of the design area or other blocks. To construct the corner stitching representation, each block in an MHS partition is given a unique label and assigned 4 pointers: *below-left* (bl), *left-below* (lb), *top-right* (tr) and *right-top* (rt) pointing to the neighboring blocks. Through these pointers, all adjacent blocks sharing their boundaries with any of its 4 sides can be found efficiently.

2.2 Non-overlap Area Constraints

In optimization, input parameters are varied within a specified range, forming a unique *candidate*. Its quality is then ranked against other candidates, among which the best ones are obtained. In compaction, the input parameters are the geometric locations of the device blocks. Each block is allowed to shift within its rectangular *placement constraints* boundary, as shown in Fig. 2(c). If block placement constraints are allowed to overlap, block positions will have *dependencies* on each others. In Fig. 3(a), the placement constraints \mathcal{C}_A and \mathcal{C}_B overlap each others, but only one block is allow to occupy any given location.

In simulation-based optimization, candidate throughput is crucial to its efficiency and quality. Temporarily accepting positional independence, and then modify or reject candidates with overlap violations incurs extra overhead, and would significantly deteriorate optimization efficiency. A more restrictive scheme with non-overlapping placement constraints is essential to allow effective combinatorial optimization. Fig. 3(b) shows the MHS partition of blocks A and B creates 3 *vacant tiles* U, V and W . A non-overlap placement constraint scheme can be constructed by horizontally bisecting V . The two halves are then merged with U and W to form the placement constraints \mathcal{C}_A and \mathcal{C}_B respectively, as shown in Fig. 3(c). To preserve symmetry properties throughout compaction, the placement constraints of mirrored block pairs are also mirrored. Definition 1 defines our placement constraint specifications derived from the MHS partition. The derivation is efficient, as constraint boundaries of each block are independent of others. It also accounts for self, mirror and perfect symmetry properties, such that they are maintained throughout every possible compaction.

Definition 1: Given the MHS partition $MHS(P)$ of a layout placement P . The placement constraint \mathcal{C}_p for each circuit block p in P is defined by a rectangular boundary computed as follow:

1. If p has no symmetry constraints, then (i) the vertical boundaries on each side of \mathcal{C}_p are the vertical bisectors of the *narrow-*

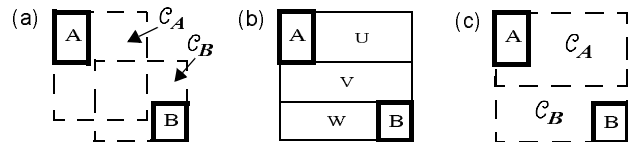


Fig. 3 (a) Overlapping block placement constraints (b) MHS partition (c) Non-overlapping constraints derived from MHS partition

est neighboring vacant tiles. If no blocks are on their opposite sides, then \mathcal{C}_p spans the entire widths of these vacant tiles. (ii) Similarly, the horizontal boundaries of \mathcal{C}_p extend to the horizontal bisectors of the of the *shortest* neighboring top and bottom vacant tiles. If the opposite sides of them are not device blocks, then \mathcal{C}_p extend to the *shortest height* among all neighboring vacant tiles above or below p .

2. If p is perfectly symmetric, \mathcal{C}_p is equivalent to the boundary of p . That is, the placement of p is fixed and would not be optimized.
3. If p is self-symmetric about vertical axis l , then \mathcal{C}_p is derived according to rule 1 stated above, except its vertical boundaries are the same as the vertical boundaries of block p .
4. If p has mirror symmetry with block p' about vertical axis l , then $\mathcal{C}_p = \mathcal{C}_p \cap \text{mirror}(\mathcal{C}_{p'}, l)$, where \mathcal{C}_p and $\mathcal{C}_{p'}$ on the right side of the equation are derived according to rule 1 stated above.

Fig. 2(d) shows placement constraints derived for various blocks of the example circuit. Blocks E and G are self symmetric and thus only vertical displacements are permitted. The top (left) boundary of Block C goes to its full height (width) of the vacant tile above (left of) it, as the object above (left of) it is also a vacant tile (the placement boundary). Both its right and bottom boundaries extend to half of its adjacent vacant tiles since blocks D and H are on the other side of them. Block H and K have mirror symmetry about the central vertical axis, their constraint boundaries are the intersection of itself and the mirror image of its partner. In other words, the rectangular placement constraints of a mirrored-pair are the mirror image pair of the more restrictive rectangle. Hence the top constraint boundary of K only extends to the same height as that of H .

III. PARASITIC MODELS

Accuracy of interconnect parasitic models for substrate coupling, interconnect and power supply parasitics are crucial for interconnect-dominated DSM designs, as the objective functions reply on them to evaluate and rank the qualities of various placement candidates.

3.1 Substrate Parasitic Model

An ideal substrate solely provides the mechanical support for all devices of the circuit, while keeping them electrically isolated from each others. Practical substrates (usually p -type) are highly

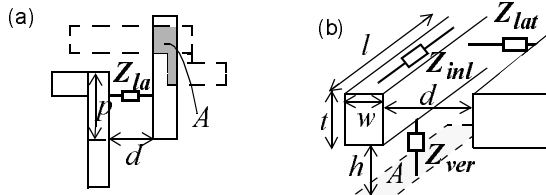


Fig. 4 Definition of interconnect parasitic model parameters

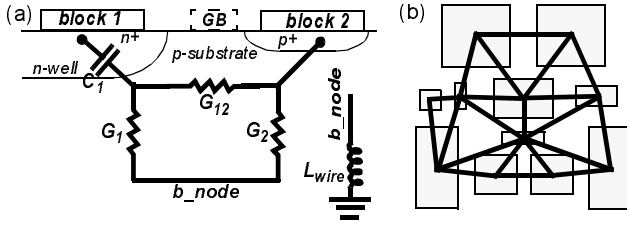


Fig. 5 (a) Substrate parasitic model (b) Epitaxial coupling paths network for G_{12}

conductive and biased to the negative power supply through the *bias* and *backplane* contacts, in order to drain any device leakage charges. Due to increased device density and shortened distances in DSM designs, leakage charges coupled to neighboring devices through the substrate can drastically affect circuit performance. [7] studies the numerical device simulation of substrate coupling between contact pairs. It concludes that substrate is resistive for signal frequencies below a few gigahertz [7]. It shows that substrate conduction is near the surface for short distance and through the bulk for longer distance.

Fig. 5(a) shows our extension to block-to-block substrate coupling model for *p*-type substrate. A unique net is assigned to each block, to be shared by body terminals of all devices within. If the block diffusion type is *n*-type or in an *n*-well, then a serial capacitance C_1 proportional to the block area is present to model the reverse biased diode junction. L_{wire} models the package bond wire inductance of the substrate backplane contact. If L_{wire} is large or the backplane is left floating, global substrate coupling will significantly degrade performance. Conductance G_{12} models short-distance block-to-block conduction near the substrate surface. As the port separation distance increases, G_{12} decreases and most charges conduct through G_1 , G_2 in the substrate bulk. To improve computational efficiency from $O(n^2)$ to $O(n)$, we set G_{12} among *non-neighboring* devices to zero.

Thus, our substrate model consists of G_1 , G_2 fixed and connecting every block to the *common* bulk node, and a G_{12} network. Fig. 5(b) shows that *Delaunay triangulation* [1], an optimal technique of $O(m \log n)$, is used to determine the neighborhood of each block, which dictates if G_{12} s are to be extracted, and if so, their values. The effect of guard band insertion is reflected by changing the substrate modeling network. During compaction, G_{12} varies exponentially with block separation distances d [7],

$$G_{12}(d) = \alpha^{-\beta d}, \quad (1)$$

where α , β are derived once for each technology from simulation.

3.2 Interconnect Parasitic Model

While maximizing the block separation distances may improve insulation from substrate coupling, parasitic resistance and coupling capacitances of critical nets may also increase. Therefore, it is crucial to find the balance among these opposing effects. Fig. 6(a) shows examples of interconnects being resized. As the relative placement of 2 blocks changes, lengths of all segments of the in-

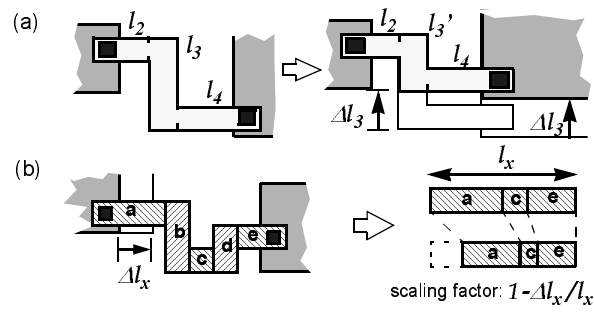


Fig. 6 (a) Interconnect reshaped as placement changes (b) Resizing is applied to all segments along the resize direction, proportional to their lengths.

terconnects parallel to the displacement direction are resized, as in Fig. 6(b). We divide the parasitic devices into three types according to their different behaviors during design changes:

1. *Inline* interconnect parasitics Z_{inl} ,
2. *Laterally-oriented* coupling parasitics Z_{lat} , and
3. *Vertically-oriented* coupling parasitics Z_{ver} .

Their values can be expressed in terms of their 1-dimensional geometric *changes* and their sensitivities. Referring to Fig. 6,

$$\begin{aligned} Z_{inl}' &= Z_{inl} + \frac{\partial Z_{inl}}{\partial l}(l-l) + \frac{\partial Z_{inl}}{\partial w}(w'-w) \\ Z_{lat}' &= Z_{lat} + \frac{\partial Z_{lat}}{\partial p}(p'-p) + \frac{\partial Z_{lat}}{\partial d}(d-d) \\ Z_{ver}' &= Z_{ver} + \frac{\partial Z_{ver}}{\partial A}(A'-A) \end{aligned} \quad (2)$$

Z_{inl} includes interconnect resistances and self-inductances along interconnect segments, it varies according to the length and width of the interconnect. Z_{lat} refers to cross-coupling capacitances and mutual inductances among neighboring objects of the same layer, it varies with their minimum separation distance d and overlapped length p . Z_{ver} denotes vertically-oriented capacitance, inductances between interconnects of different layers. It is proportional to the overlapped area A . Layer thickness t , wire width w , block area A and separation distance h are fixed throughout compaction.

IV. IMPLEMENTATION AND EXPERIMENTAL RESULTS

Our compaction scheme is based on simulated annealing, evaluating objective functions expressed by geometrically parameterized parasitic functions and performance parasitic sensitivities. The major steps are summarized as follow:

Initialization: Parasitic extraction and interconnect sensitivity derivation.

1. Import placement, routing and device symmetry rules.
2. Compute block placement constraints.
3. Compute optimum blocks compaction.
4. Export placement and update parasitic values.
5. Update extracted netlist and verify performance improvement.

4.1 Simulated Annealing

Simulated annealing is a widely used optimization approach to overcome local minima in highly nonlinear design spaces. Details of our implementation for compaction are summarized in Algorithm 1. The algorithm begins at an arbitrarily chosen candidate in the compaction space (line 2). A new candidate is drawn from a multi-dimensional bounded Gaussian distribution function $\mathcal{N}(x_0, \sigma)$, where the mean x_0 is the current value for each parameter, and σ is controlled by the neighborhood *radius* (line 5). At radius value of 1.0, the entire range spans 6σ . Lowering the radius results in a more focused search. For each newly generated candi-

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1. Procedure compaction_update:
   // Input: MHSplacement, symmetry, compaction constraints
   // Output: list of best compaction configurations
2. (temperature, intconn, cand) = Init(placement, constraints)
3. for i from 1 to number_of_iterations:
4.   newname = Namer()
5.   newcand = Nextcand(bounds, cand, radius)
6.   newcost = Cost(Placement, interconn, cand)
7.   if AcceptHillClimb(temperature, cost, newcost):
8.     best_cands.append((newcost, newname, newcand))
9.     best_cands.sort()
10.    cand = newcand
11.    if length(best_cands) > num_top_cand:
12.      best_cands = best_cands[1:num_top_cand]
13.      cost = LowestCost(best_cands)
14.      temperature = Cooling(temperature)
15. return best_cands

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Algorithm 1: Compaction optimization algorithm

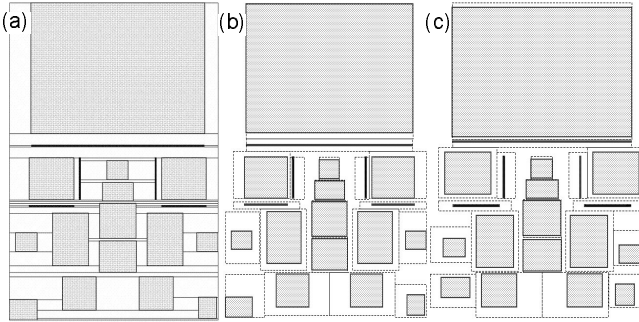


Fig. 7 (a) Initial placement with MHS partition (b) Placement constraints (c) Placement after compaction optimization

date, its impact to the circuit performance is evaluated and compared to the lowest cost candidate currently found (line 7). The candidate is accepted if the cost difference ΔC satisfies

$$e^{-\Delta C/T} > P, \quad (6)$$

where P is drawn from the uniform distributed interval $[0, 1]$. If the new cost is lower, $e^{-\Delta C/T} > 1$, acceptance is thus guaranteed. A linear *cooling schedule* is used in our implementation, which gradually lowers the virtual temperature T as the search progresses (line 14). This reduces the likelihood of (6) to be satisfied for steps that increases cost $\Delta C > 0$. Upon reaching the pre-determined number of iterations, the algorithm returns with a list of the lowest cost compaction configurations.

4.2 Cost Functions

Circuit simulators facilitate calculation (e.g. *.SENS* in SPICE) of both the DC operating-point and AC small-signal sensitivities $\partial f/\partial x$ of an output variable f with respect to any circuit parasitic values x . The cost function with respect to f is

$$C_f(x) = \frac{1}{f + \partial f/\partial x^t \cdot \Delta x}. \quad (7)$$

Δx results from block displacements are computed according to (1) and (2) for the substrate coupling network and interconnect parasitics respectively.

4.3 Compaction Optimization Examples

An analog operational amplifier circuit with 15 device blocks and 5 guard bands is shown in Fig. 7(a). It has 7 self-symmetry and 4 mirror symmetry constraints. 10 optimization trials each with 2000 iterations are performed. Parasitic cost reductions are shown in Fig. 8. An interesting observation is that the ultimate optimization results have some dependence on the starting points. Hence, it is advantageous to break down long iterations into several trials that restart at a new state. The placement of the best compaction candidate is shown in Fig. 7(c). Guard bands placements are si-

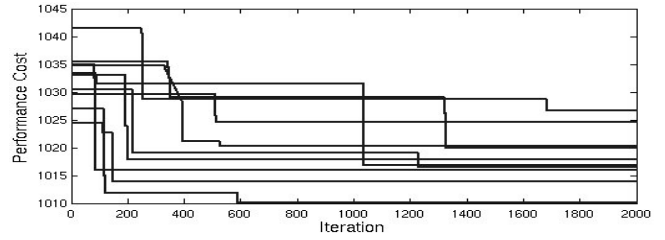


Fig. 8 Cost decrement of optimization trials with arbitrary initial candidates

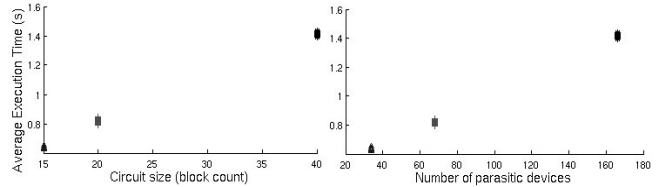


Fig. 9 Optimization efficiency of various circuits

multaneously optimized. The average execution time is 6.006s for 2000 iterations on a UNIX computation server.

In order to examine the efficiency of the algorithm, 3 analog circuits of various sizes are optimized. Each design is propagated with 10 sets of randomly generated performance sensitivities, in order to represent distinctive circuits of the same size. Each set is optimized 50 times for 200 iterations. Fig. 9 plots the average execution time versus the circuit block and parasitic device counts. Expectedly, the execution time depends linearly on the total number of parasitic devices, instead of block count nor circuit types, as most time is spent by performance cost computation.

V. CONCLUSIONS

A compaction algorithm that optimizes the placement of guard bands and circuit blocks for analog circuits using simulated annealing technique was proposed to minimize layout parasitic effects for analog circuits in the DSM mixed-signal environment. Through the use of sensitivity-based cost functions, the impact of interconnect and substrate parasitics are quantified. Performance improvement is demonstrated while the customized layout topology, symmetry and matching constraints are preserved.

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