SONR based layout decomposition and applications

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ABSTRACT

As the integrated circuit (IC) technology development moves forward, the design becomes more and more complicated, and the chip size becomes larger and larger. It's getting more challenging to analyze the design and detect the potential manufacturing issues in an efficient way. The layout decomposition brings the possibility and flexibility to address the above challenges as the unique patterns after layout pattern decomposition reduce the number of wafer measuring sampling points and give the best coverage of the layout for a quick and effective design check. In this paper, we'll introduce Siemens EDA's machine learning technique named SONR for the layout decomposition and how it can be used to reduce OPC recipe development and tape-out cycle time.

INTRODUCTION

State of nature reduction (SONR) is a clustering tool that was invented to find the best representatives with the similar coverage as the full dataset. SONR is a feature-based tool, and it has multiple platforms that satisfy the requirement of different applications. In this paper, we focus on the layout decomposition application and how SONR is used for pattern clustering. Calibre SONR is characterized by its powerful built-in features and the customized features, which are used to capture the most significant manufacturing signature and yield a more desired grouping result.
The OPC recipe development usually starts with some layout samples with limited area to get a fast turnaround time. How to sample the design to obtain a better representative clip for the OPC recipe development is critical. In this paper, we innovatively decompose layout and classify patterns with Calibre SONR for good sampling points on the chip, and use machine learning technics to choose the best coverage patterns on the chip, by clustering them with specific algorithm. SONR is used to compress the area by selecting unique pattern, reduce the consumption of resource and runtime, and accelerate the flow of OPC recipe development and tape-out cycle time.

SONR APPLICATION

Calibre SONR can be used for hotspot prediction and pattern analysis. In the layout decomposition application, we mainly utilize SONR for pattern clustering. User picks the proper feature sets based on the application and the information they have. As shown below in Figure 1, these features are extracted from layout dimensions, pattern density, DFM properties, interlayer features, contour dimensions, image intensity measurements and OPC mask measurements, and then these features are combined to form a unique pattern fingerprint which is used as input of machine learning in SONR.

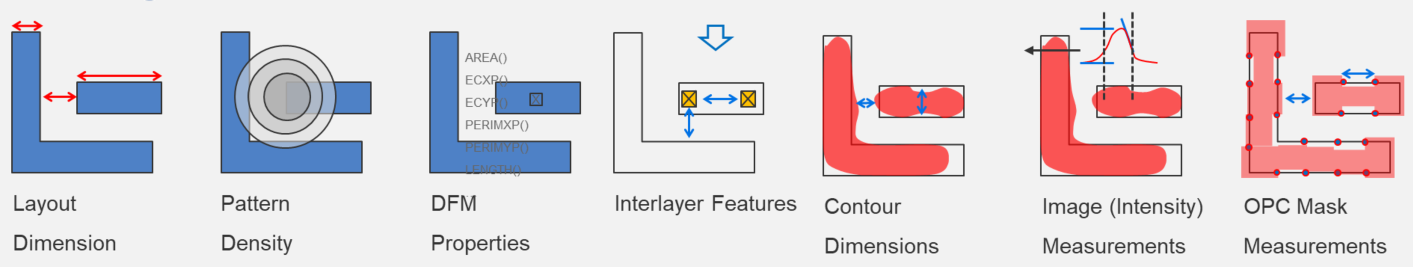

Figure 1. The source of the SONR features

After feature collection, all the information is saved in Calibre-specific Machine Learning DataBase (MLDB). The feature vector of MLDB is passed to SONR unsupervised clustering ML model generation for clustering. Due to the possible correlation between the features, the clustering process is done in SONR domain. Not all the dimensions are equally important in SONR domain, so the clustering is done on a hierarchical tree called SONR tree. At the end level(leaf) of the SONR tree, all the patterns inside the same node are considered to have similar feature signature. Compared to all the commercial clustering algorithm, SONR clustering provides better or similar accuracy of the coverage, but with much better performance – to cluster a 300-million vector database with 37 million unique feature vectors with 47 features, SONR cluster method only took 90 mins. To have good coverage, the one representative is picked from each of the nodes.
As shown in Figure 2, the SONR machine learning platform gets information from design and process. It collects features from a single test chip or multiple production chips. It includes information from multiple layer interaction, lithography and etch process and even stress issues. With the extracted features from the layout, models, or OPC recipes, SONR builds Supervised, Semi Supervised or Unsupervised patterns clustering depending on the requirements from different applications.

Together with the usage of MLDB, SONR is helpful in pattern reduction, pattern coverage, model coverage, layout comparison, Hotspot prediction, and defect classification.

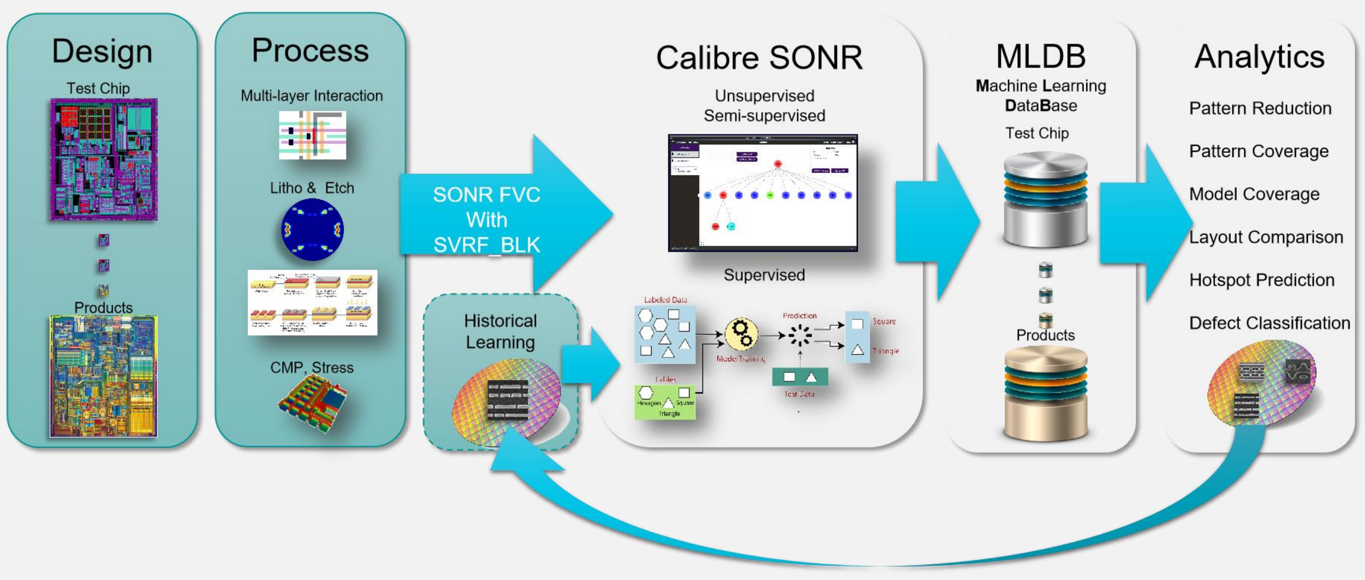

Figure 2. The flow of SONR application

In the early OPC recipe development stage, the developers usually clip a layout for recipe turning with a fast turnaround time, but how to make sure that the clips are the best representatives that cover the variation of the full chip remains to be a challenge. Is there a way to select the best representative patterns with an acceptable area for a fast runtime? Figure 3 is an example of SONR clustering result - SONR tree. The cost function in SONR helps determine the fuzziness of the result, and in this case, we use the number of cluster number. Users can adjust the number of clusters according to the maximum area from the OPC recipe tunning budget. Since the patterns are similar in the same tree node, if one of the patterns is identified as hotspot, the other patterns in the same tree node have high possibility to be the potential hotspots due to the signature similarity. And the same or similar adjustment of OPC recipe is expected to fix all the problematic patterns in the same node.

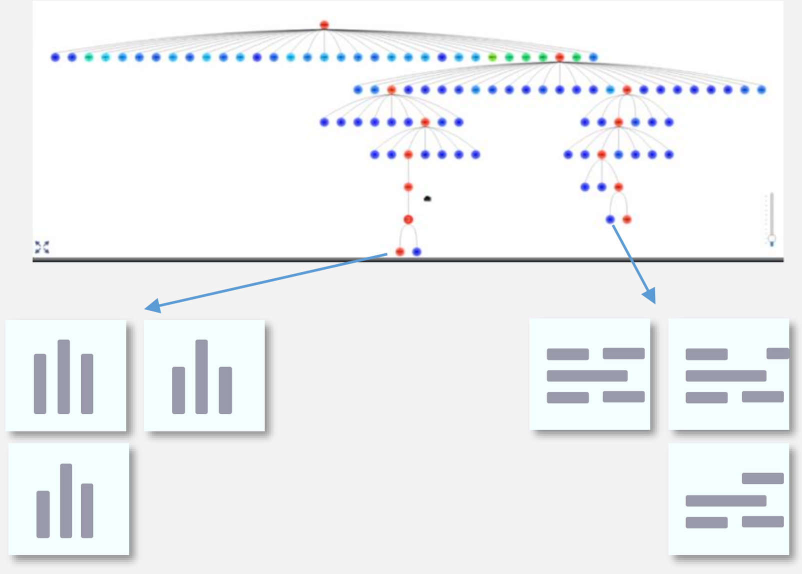

Figure 3. The structure of SONR tree

EXPERIMENT AND RESULTS

In our experiment, the test case is Metal1 (M1) layer of a logic chip, the pitch of the pattern is 0.162um, SONR is used for logic chip layout decomposition and classification.
As shown in Figure 4, SONR could reveal the smallest area, almost 19% of the chip area to achieve 100% hotspot hit rate. When halo size is smaller than 1.5*pitch, geometry-based grouping is meaningless. However, SONR's feature vectors consider large range to capture the impact from the neighboring layout, and the reduction relies on the fuzzy setting - the target clusters in this case. In the figure, we can see less than 4% chip area, near 40% hotspots are still seen. From SONR Tree's point of view, in the same tree node, if an adjustment of recipe is done to fix one of the hotspots, the other hotspots that have the similar signature may be fixed as well, so when looking at 40% hotspots, more hotspots can be fixed in the end.

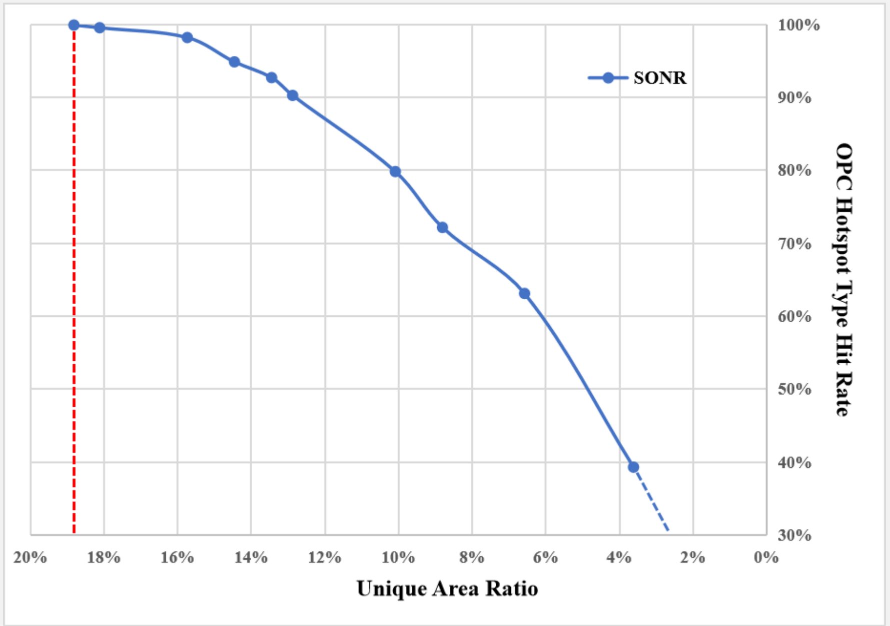

Figure 4. The relationship between OPC hotspot type hit rate and unique pattern compression ratio.

From the result of our experiment, we concluded that SONR provides a better way of fuzzy clustering for hotspots fixing and it is a good solution for further pattern compression. This machine learning tool achieved a high hotspot type hit rate and gave the best coverage of the patterns. SONR can handle large data with low requirements of memory and runtime, and significantly reduce the OPC recipe development and product tape-out cycle time. We expect that in more advanced process node, SONR plays a more significant role in accelerating tape-out cycle time.