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Analog circuit design space description based on ordered clustering of feature uniqueness and similarity

COMPUTER AIDED DESIGN PROJECT 2

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Contents

Introduction

This project is based on the paper "Analog circuit design space description based on ordered clustering of feature uniqueness and similarity" where the paper introduces a novel approach to express the principle similarities and difference between a set of analog circuits. This comparison is used to synthesize topologies or improves existing circuits to incorporate useful features from other designs or to identify common characteristics that can be reused for broad sets of performance requirements.

There are few displaying strategies that portray a populace of circuits to show the likenesses and contrasts in their topological and behavioral elements and their effect on execution. The portrayals of circuit populaces can offer a thorough introduction of the outlines pace secured by the plan set, the adaptability of configuration components when utilized under different imperatives, and the uniqueness of elements in handling necessities. The comparison helps understanding the performance advantages and limitations of a circuit topology compared to another. Circuit macromodels depicts the relations or mathematical dependency of voltages and current at circuit nodes on design variables such as transistor dimensions. There are models in the literature which address a large variety of performance attributes. Techniques used for such purposes include regression analysis, symbolic analysis, model-order reduction. These models are used for verification purposes, design and synthesis. Four division scores, based on entropy, item characteristics, classification characteristics, and Bayesian classifiers, were considered to deliver clustering strategy that offer understanding about the uniqueness and significance of features in setting AC execution and additionally the restricting elements of the designs. Clustering can be considered the most important *unsupervised learning* problem; so, as every other problem of this kind, it deals with finding a *structure* in a collection of unlabeled data. Clustering can be defined as "the process of organizing objects into groups whose members are similar in some way". A *cluster* is therefore a collection of objects which are "similar" between them and are "dissimilar" to the objects belonging to other clusters. Following simple graphical example depicts the clustering:

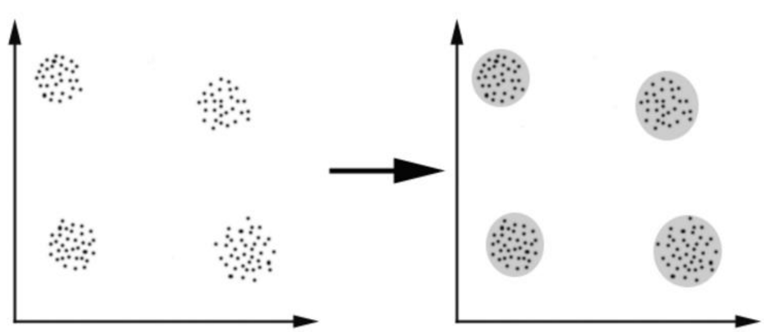


Fig1. Clustering Depiction

The goal of clustering is to determine the intrinsic grouping in a set of unlabeled data.

This paper deployed a technique called Ordered Node Cluster Representations(OCNR) for creating aforesaid models to find out the similarities and dissimilarities among the analog circuits. This modelling methods has the given three steps (i) identifying the possible separation criteria, (ii) analyzing the criteria with respect to their potential of grouping the circuits, and (iii) building ONCRs such that the separation of dissimilar circuits is maximized.

Fig. 2 illustrates the symbolic representation of a set of circuits. Each circuit is described by the set of its nodes. Delivering a component bunching plan for the arrangement of circuits must (i) distinguish the way of criteria utilized as a part of discovering similarities and dis-similarities between the circuits and (ii) locate the topological highlights that understand the similarities and dissimilarities. The similar nodes are circled together and form a group Gi of similar features, with respect to their pole and coupling to other nodes expressions.

The common and dissimilar node features presented in the representation are related to the relevant performance attributes Perf i. For example, for AC domain, the shared node features represent the common symbolic expressions of the poles at the nodes, and the analyzed performance Perf i defines the position of the common pole on the magnitude and phase response of the circuit.

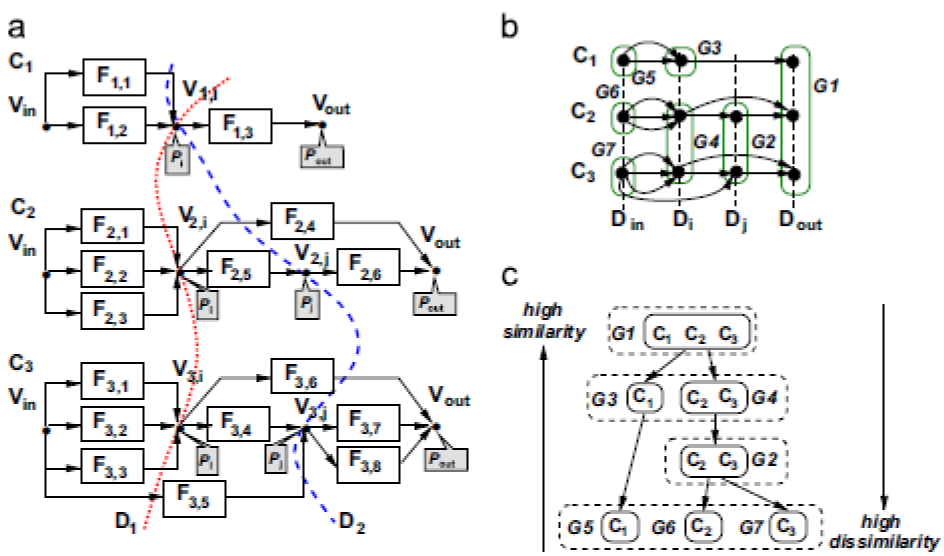


Fig2. SFG depicting the problem and results

SEPARATION SCORES: The following four features with the given mathematical formulation were used assign circuits to a cluster:

1. Entropy: Entropy is used to describe similarities and differences between circuits, and is popular for classification in data mining. We define a cluster's in formation content as follows:

$$S_0(Cl_k) = -\sum_{i=1}^{N} p_i \log_N p_i$$

N is the total number of circuits with nodes in cluster Cl_k, and pi is the probability that a circuit in cluster Cl_k is associated with a group of matched nodes. For each group G_j of matched nodes in cluster Cl_k, the probability is expressed as $|G_j|/|Cl_k|$.

The metric is greatest when each circuit hub shapes its own gathering. It demonstrates zero coordinating, or that the individual hubs are different from each other and shape their own gatherings inside the group.

2. Item Characteristics: This measure maximizes the inference potential of attributes. The score of a matched cluster Cl_k is expressed as:

$$S_1(Cl_k) = \frac{p_k N_k}{(1-p_k)+p_k N} \prod_i \left(\frac{N_{k,i}}{Card_k}\right)$$

where p_k is the probability of selecting a node and a group from cluster Cl_k, when there are N total groups in the matching solution and N_k groups of nodes in cluster Cl_k. Card k is the total number of groups in the cluster, and N_k; i is the number of nodes in group G_i of cluster Cl_k.

3. Category Characteristics: The score of a matched cluster Cl_k is expressed as follows for a cluster on basis of category characteristics

$$S_2(Cl_k) = p(Cl_k)\left(\sum_i p(G_i|Cl_k) - p(G_i)\right)^2$$

where Cl_k is the cluster probability and is related to the total number of clusters in the matching solution N_c. Like Eq. (8), N_k is the total number of groups in cluster Cl_k, and N_k; i is the number of circuit nodes in group G_i of cluster Clk. Card k is the number of nodes in the cluster, N_n is the total number of nodes in the matching solution, and N is the total number of groups in the solution.

4. Bayesian Classifiers: For this scheme, score is calculated as

$$S_3(Cl_k) = p(Cl_k|G_i) = \frac{p(G_i|Cl_k)p(Cl_k)}{p(G_i)}$$

Where

$$p(Cl_k) = \frac{1}{N_c}$$

$$p(G_i|Cl_k) = \frac{\prod_i N_{k,i}}{(Card_k)^{N_k}}$$

$$p(G_i) = \frac{Card_k}{N_n} \cdot \frac{N_k}{N}$$

Where each term means same as defined above.

Description of the method presented in the paper

UBBB MODEL: The circuit highlights utilized as a part of grouping are recognized from a basic model of simple circuits, called Uncoupled Building- Block Behavioral model (UBBB). The models express the symbolic reliance between the circuit topology and the AC behavior of the circuits, including poles at circuit nodes and nodes coupling. Using the circuit topologies would make clustering more difficult as the dependency are indirectly related. UBBB models are directed signal flow graphs for which vertices correspond to circuit nodes and their associated poles and edges capture the signal coupling between nodes. The coupling between two nodes is of two kinds: direct influences between the nodes and decoupled, equivalent influences between signal inputs and other circuit nodes. This UBBB model represents the first step in the given algorithm.

Algorithm given in the paper:

(1) Produce the circuit representation for the considered performance;

(2) Produce the set of possible classifications curves Di;

(3) If an ordering criterion exists for curves then order curves Di;

(4) For all curves Di (following their order) compute the separation cost for clusters of Di;

(5) For all curves Di in increasing order of their separation cost build ONCR level by adding nodes for clusters of curve Di;

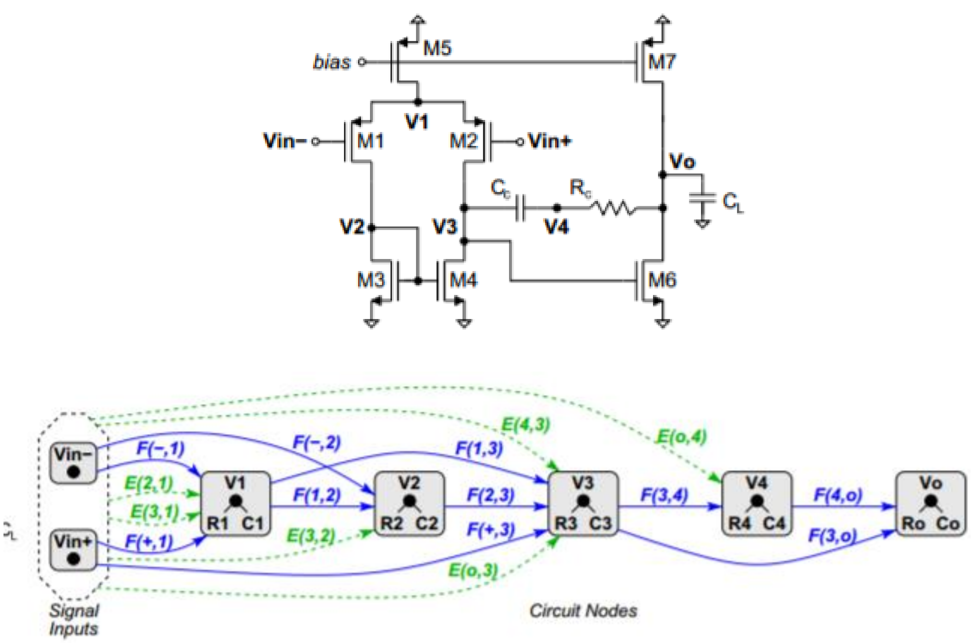


Fig3. Schematic and UBBB model graph for a simple two-stage amplifier

SEPARATION CRITERIA FOR CLUSTERING

In the paper, there are four separation criteria to order the matched clusters. The ordered feature clustering for five OpAmps are shown in the figure below:

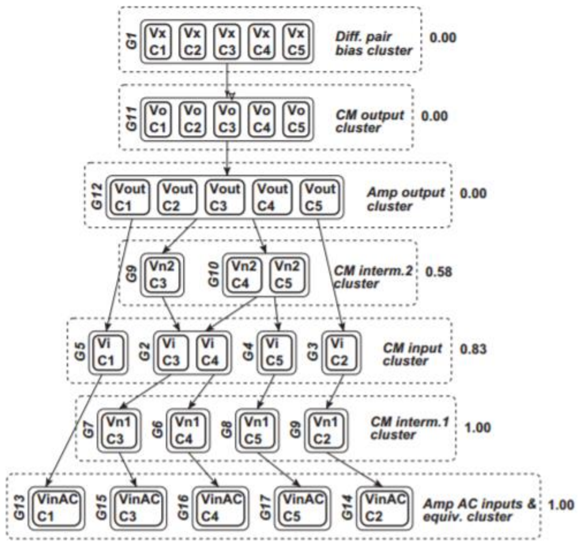


Fig4. Entropy-based ordered feature clustering (OCNR) for five OpAmps

Description of implementation

We have proposed the following implementation to find the similarities and dissimilarities between analog circuits.

STEP1: IDENTIFY THE BUILDING BLOCKS IN THE CIRCUIT

Given a set of circuits, each circuit is represented in the form of graph(hypergraph). Using the recognition algorithm, all the building blocks in the circuit are searched with the hierarchy of library. This algorithm divides the graph of circuit into a number of subgraphs and are compared with the library of building blocks.

STEP2: PRODUCE THE SET OF DIFFERENT BUILDING BLOCKS AND GROUP THE CIRCUITS THAT INCLUDES THEM.

Each circuit instance stores the building blocks present in it. This instance later forms a group in the cluster of building blocks as shown in the code below:

```
ClusterNode c;
List<String> bb_list = ckt.getBuildingBlocks();
Iterator<String> i = bb_list.iterator();
while (i.hasNext()) {
   switch (i.next()) {
       case "Differential Pair":
              dp.add(ckt, "Differential Pair");
              ListBB.getInstance().addNodeCount(dp, dp.getCount());
              break;
```

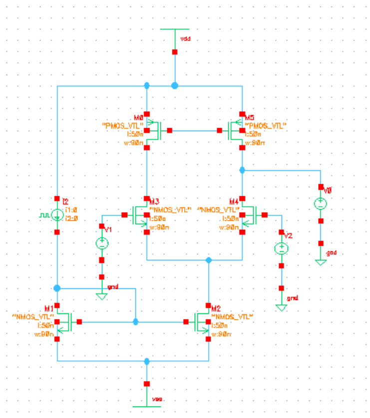
STEP3: FOR ALL BUILDING BLOCKS, COMPUTE THE SEPARATION COST FOR CLUSTERS OF BUILDING BLOCKS.

There are four methods implemented in this project to calculate the separation score metrics: entropy, item characteristics, category characteristics and Bayesian classifiers. The code snippet for one of the methods is shown below:

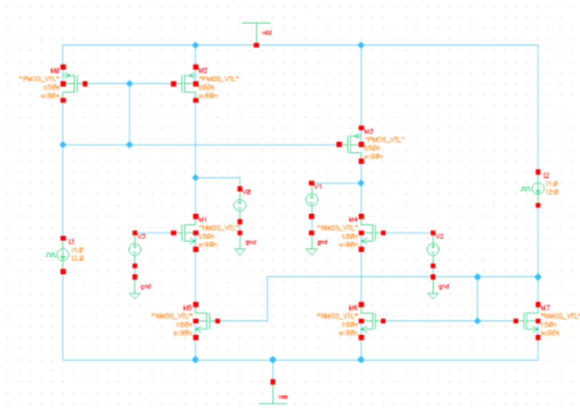
```
public double calculateEntropy() {
		double numCluster = ListBB.getNodeCount();
		double prob = 1 / numCluster;
		double entropy = 0;
		Collection<Integer> n_k = ListBB.getInstance().getValue();
		Iterator<Integer> n_ki = n_k.iterator();
		while (n_ki.hasNext()) {
			double newValue = n_ki.next();
			entropy += (-1 * ((prob * newValue) * (Math.log(prob *
newValue) / Math.log(numCluster))));
		}
		return entropy;

	}
```

Experimental Results

The experiment consider a set of 7 analog circuits. The netlist for these circuits is produced using Cadence Virtuoso. The schematics and the experimental results are shown below:



a)



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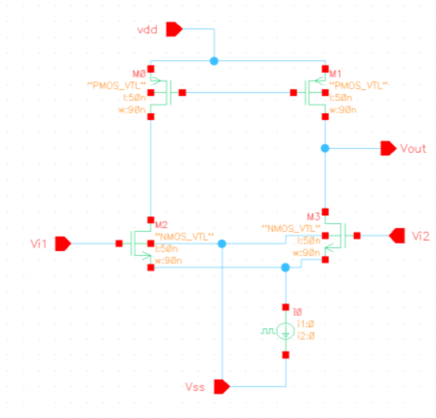

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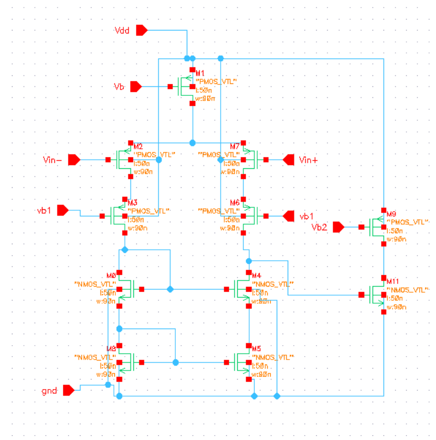
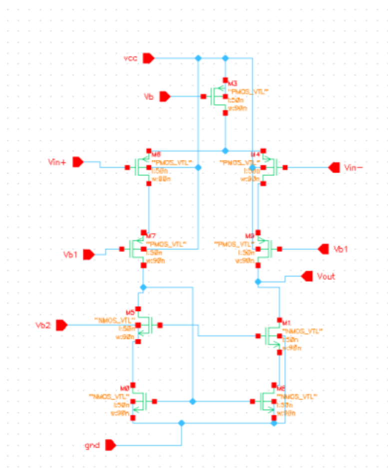
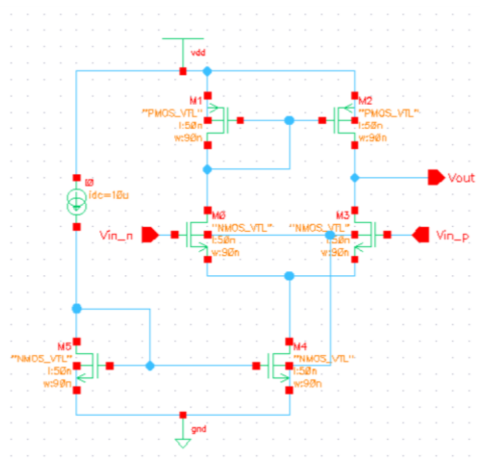


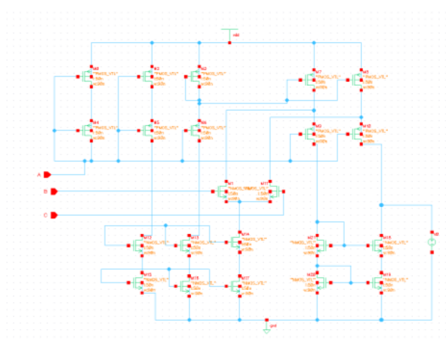
d)



e)



f)



g)

Fig5. (a)Active Load DP; (b) Differential Pair with Active load; (c) Cascode Amplifier (d)High gain cascode Amplifier; (e) Cascade amplifier; (f) Differential Amplifier(g) Folded Cascode Opamp.

Table1. Detected Building Blocks for Given Circuits

S.No	Circuit	Building Blocks
1.	Active Load with Differential Pair	Differential Pair, Current Mirror
2.	Two stage Current Amplifier	Current Mirror, Current Mirror, Voltage Controlled Current Source
3.	Folded Cascode Opamp	4-transistor Current Mirror, Level Shifter, Current Mirror, Level Shifter, Differential Pair
4.	Differential Amplifier	Differential Pair, Level Shifter, Current Mirror
5.	High Gain Cascade Amplifier	Cascode pair, Differential Pair, Voltage Controlled Current Source, Current Mirror
6.	Cascode Amplifier	Current Mirror, Current Mirror, Voltage Controlled Current Source, Cascode Pair, Cascode Pair
7.	High Gain Amplifier	Differential Pair, Voltage Controlled Current Source

Table2. Clustering and Separation costs

S.No.	Cluster	Node	Entropy	Item Char	Category Char	Bayesian Classifier
1.	Differential Pair	5	3.3	0.57	0.50	0.625
2.	Current Mirror	9	4.5	1.13	0.72	0.7815
3.	Level Shifter	2	2.3	0.34	0.23	0.435
4.	Cascode Pair	2	2.2	0.34	0.21	0.435
5.	Wilson current mirror	1	1.0	0.10	0.17	0.207
6.	Voltage Controlled Current Source	3	3.2	0.46	0.32	0.243
7.	4-Transistor Current Mirror	1	1.0	0.12	0.18	0.21

Conclusion

In this project, we implemented the possible sets of building blocks present in an analog circuit that was later used to generate models called Ordered Node Clustering Representation (ONCR). Four separation scores were studied for circuit feature clustering; Entropy, Item Characteristics, Category Characteristics and Bayesian Classifier for a set of circuits.

References

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