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Incorporating Knowledge in Genetic Algorithms for Device Synthesis

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Abstract

In this paper, the knowledge of qualitative relations between device parameters and characteristics, are incorporating to guide genetic algorithm to exploiting in the promising space. It makes device synthesis be more efficiently in searching for feasible design space, which satisfies the desired characteristics.

Introduction

To design devices with desired characteristics is an important step in TCAD for technology synthesis [1]. It needs a synthesis methodology to get workable devices automatically instead of the conventional approach that by employing design of experience (DoE) [2], which needs the experts to tune design parameters.

Device synthesis is a nonlinear programming (NLP) problem, which can be performed through searching over the design space specified by designers. The requirements include: 1) because no explicit objective functions between parameters and characteristics are available for short channel devices, a global search strategy instead of gradient-based strategy should be employed to find the feasible results; 2) because there exists process deviation for each device parameter, to identify a workable device, it is necessary to find a feasible region that satisfied all constraints by the desired characteristics instead only a feasible point.

In our previous work [3], a prototype system for device synthesis is realized with a genetic algorithm, called GENOCOP [4], by calling device simulator to search feasible device parameters in the design space. It has been used to synthesis a FIBMOS device.

However, the calculation times should be decreased because device simulator is time-consumptive. This work is focused on studying the methodology of incorporating knowledge in genetic algorithms to reduce calculation times. Since the knowledge of qualitative relations between device parameters and characteristics, which are monotonous in common, can guide genetic algorithms to exploiting in the promising space. The results show this methodology can improve the performance of device synthesis system efficiently.

Prototype system for device synthesis

The prototype synthesis system is summarized in Fig.1.

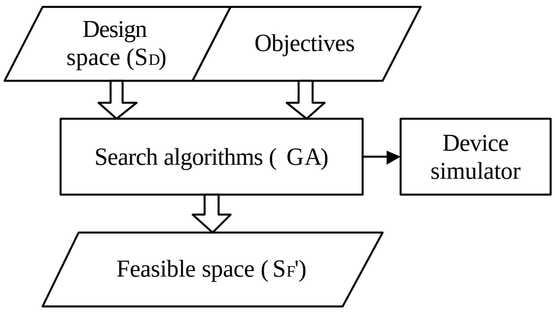

Fig. 1 System architecture of prototype system

The input parameters of genetic algorithms include:

a) Design space (**S_D**), is a hyperspace that defined by a set of design parameters with the bounds. In this work, in order to prevent the found feasible points to be too clustered to represent a big feasible space, each parameter is divided by specified step (the magnitude about of process deviation is suitable) to discrete S_D as an integer-value space. Each individual is a grid point.

b) Objectives (include constraints) to specify the desired characteristics. We classify the objectives into:

- MIN, minimize the objective value;
- LET, the objective is less than a specified value;
- REG, the objective is constrained in a region.

Where the LET and REG are constraints.

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Definition 1: The space in S_D that satisfying all of the constraints is denoted as feasible space (**S_F**). The infeasible space (**S_I**) is the supplementary space of S_F in S_D. The summary of current found parts in S_F is **S_F'**, and the summary of current found parts in S_I is **S_I'**.

The mission is to find feasible points more fast, and make S_F' similar to S_F. For MIN objective, we consider the better solutions in S_F'.

Incorporating knowledge in GA (IKGA)

Basic principle

Suppose there have *n* parameters and *m* objectives.

The matrix of relations **M_{DT}** ($m\times n$)

Each element m_{dt} in M_{DT} is a relation between a parameter and an objective according to known knowledge. It defines the variety tendency of the characteristic value for an objective while the value of a parameter is increased, which includes four statuses:

- CONSTANT, no change;
- INCREASE , increasing;
- DECREASE, decreasing;
- UNKNOWN, unknown by users.

Variety tendency of design parameters **V_D** ($n\times 1$)

Each element v_d in V_D represents how the current parameter value will be varied. It includes four statuses:

- CONSTANT, no change;
- INCREASE , value increases;
- DECREASE, value deceases;
- UNKNOWN, unknown status (not be used).

Variety tendency of characteristics **V_T** ($m\times 1$)

Each element v_t in V_T represents how the characteristic of an objective will be varied. It includes four statuses:

- CONSTANT, no change;
- INCREASE , value increase;
- DECREASE, value decease;
- UNKNOWN, unknown by users.

Calculation laws from V_D to V_T

If the M_{DT} and V_D are known, the following equation is used to calculate V_T:

$$M_{DT}V_D = V_T \qquad (1)$$

The operations between the elements include:

Add operations:

UNKNOWN + * = UNKNOWN,
CONSTANT + * = *,
INCREASE + DECREASE = UNKNOWN,
* + * = * (2a)

And multiply operations:

CONSTANT · * = CONSTANT,
INCREASE · * = *,
DECREASE · DECREASE = INCREASE,
UNKNOWN · * = UNKNOWN
(If * != CONSTANT) (2b)

The operations satisfy the exchange law. The * represent any elements.

Property 1: If the relation of ith (i<m) objective to jth (j<n) parameter is equal to UNKNOWN, and the jth element in V_D is not equal to CONSTANT, then the ith element in V_T will be equal to UNKNOWN.

Needed variety tendency of objective **V_O** ($m\times 1$)

Each element v_o in V_O represents how the value of an objective should be varied to become an feasible objective. It includes four statuses:

- CONSTANT, not need be changed;
- INCREASE , need to increase;
- DECREASE, need to decease;
- UNKNOWN, can be changed arbitrary.

Two steps are used to get the V_O:

a) Get objective relations **R_{tcd}** ($m\times 1$)

Each element r_{tcd} in R_{tcd} represents the magnitude between the current characteristics value (v_{cv}) and the desired characteristics value (v_{dv}) for an objective. It includes four statuses:

- X, can not compare (for a MIN objective);
- EQ, i.e. $v_{cv} = v_{dv}$;
- LA, i.e. $v_{cv} > v_{dv}$;
- LE, i.e. $v_{cv} < v_{dv}$.

b) Get V_O from the types of objectives

From the table 1, we can get the element v_o by the element in R_{tcd} and the type of each objective.

Table 1. v_o in different r_{tcd} and objective types

	MIN	LET	REG
X	DECREASE	-	-
EQ	-	DECREASE	UNKNOWN
LE	-	DECREASE	INCREASE
LA	-	UNKNOWN	DECREASE

Find infeasible and feasible space

Definition 2: For an element in V_T and an element in V_O, if one of them is equal to UNKNOWN, then define the two elements are similar to each other.

Definition 3: If all the elements in V_T are similar or equal to the corresponding elements in V_O, then defines V_T is similar to V_O.

Property 2: For an individual, a V_D will create a V_T, if V_T is not similar to V_O, then the space that specified by V_D is infeasible space.

Property 3: For a feasible point p1, if all the elements in V_T from a V_D are not equal to UNKNOWN, and another feasible point p2 is belong to the space that specified by the point p1 and the V_D, then the child space that the bound are specified by the p1 and p2 is feasible space.

Robust calculation and times reduction

Definition 4: For a M_{DT}, a variety of V_D and the calculated V_T are defined as a relation couple (**C_{DT}**).

Definition 5: For the V_T in a C_{DT}, if one of the elements is not UNKNOWN, then defines it as an effective relation couple (**C_{EDT}**).

Definition 6: For a matrix that is constructed by some rows and columns of M_{DT}, if it includes no UNKNOWN elements, then defines it as a child determinate relation matrix (**M_{CDT}**).

Definition 7: If a M_{CDT} is not a subset of any other M_{CDT} of M_{DT}, then define it as a maximum child determinate relation matrix (**M_{MCDT}**).

To find C_{DT}s for a M_{MCDT} that constructed by n' parameters (n' =n) and m' (m' =m) targets, the V_D' is treated as a child scheme of V_D, while the other n-n' parameters of V_D are set to CONSTANT.

Property 4: The set of C_{DT}s of all the M_{MCDT} represent all the C_{EDT}s of M_{DT}.

Realization of IKGA

The program diagram of IKGA is shown in fig. 2.

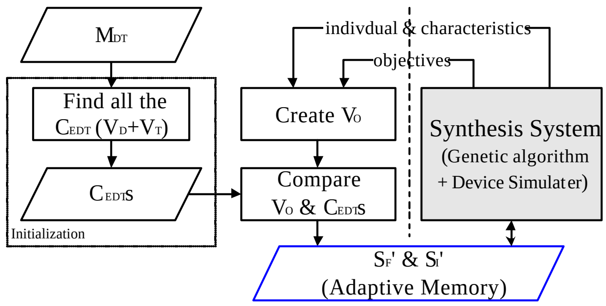


Fig. 2 Principle diagram of IKGA

On the initial stage, we find and store all the C_{EDT}s for given M_{DT}. When GA creates a new individual, device simulator is used to get the characteristics. With the information of objectives, we can create the V_O. If the individual is infeasible, then the V_O is compared to the stored C_{EDT}s and gets the infeasible space according to property 2. If the individual is feasible, then check all the other feasible points, and get the feasible space according to property 3. The found S_F' and S_I' are used to accelerate the evolution.

An adaptive memory is employing in GENOCOP to manage all the found infeasible space S_I' and feasible spaces S_F', which are used to guide performing genetic operations in the promising space, while the points that located at the boundary of the S_I' or S_F' are selected as parents with large probability.

Results

The different M_{DT}s in table 2 are used to test IKGA (the case iiii can be seemed as original genetic algorithm). The other algorithm settings are same, for each M_{DT}, the algorithm is performed 11 times (runs) and the least favorable one is disregarded.

Table 2. The different M_{DT} for IKGA

	Leff	Tox
Ion	DECREASE	DECREASE
Ioff	DECREASE	DECREASE

(i)

	Leff	Tox
Ion	UNKNOWN	DECREASE
Ioff	DECREASE	DECREASE

(ii)

	Leff	Tox
Ion	UNKNOWN	UNKNOWN
Ioff	DECREASE	DECREASE

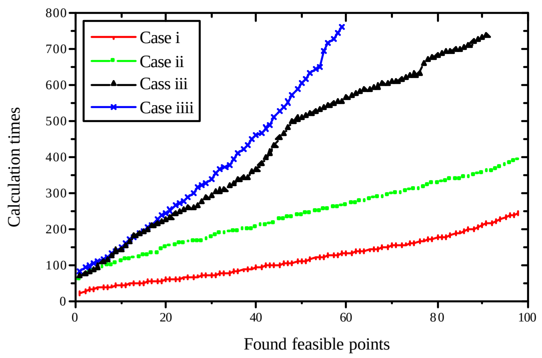
(iii)

	Leff	Tox
Ion	UNKNOWN	UNKNOWN
Ioff	UNKNOWN	UNKNOWN

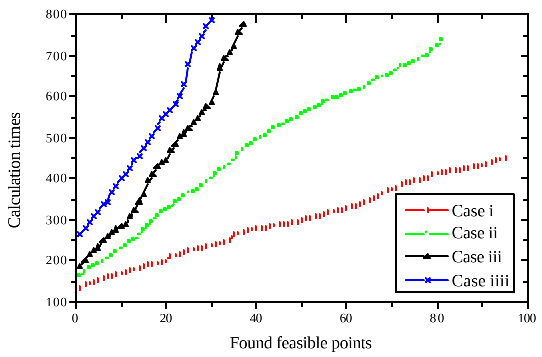
(iiii)

The example is design a MOS device, which the design parameters include channel length L_{eff} that is 0.35 ~ 0.45μm and oxide thickness T_{ox} that is 0.0025 ~ 0.0075μm, and the desired characteristics include the drive current I_{on} and off-state current I_{off}. The acceptable relative error is set to 1%. Two conditions for different S_F/S_D are tested:

a) I_{on}=2e-3A, I_{off}<4.3E-13A. S_F/S_D=98/10201
b) I_{on}=2e-3A, I_{off}<4.04E-13A. S_F/S_D=144/1002001



a) S_F/S_D=98/10201



b) S_F/S_D=144/1002001

Fig. 3 Number of feasible points vs. calculation times with different M_{DT}s

Fig. 3 shows the relations between the number of feasible points and the average calculation times in different M_{DT} for different S_F/S_D. It can see more elements that are not UNKOWN in M_{DT} can make the algorithm to perform searching efficiently, not only the first feasible point, but also a set of feasible points that are used to describe S_F'.

Conclusion

In this paper, we have proposed IKGA, an efficient and robust algorithm by incorporating knowledge in genetic algorithms to identify the feasible and infeasible space efficiently. The adaptive memory feature allows the implementation of procedures that are capable of searching the solution space economically and effectively. It is suitable for synthesizing the semiconductor devices, because many relations between device parameters and characteristic are monotonous.

Further explorations may concentrate on incorporating: 1) the single-peak relation, which is the second frequently relation between device parameters and characteristics, by identifying the monotonous parts; 2) linkage learning [5] for UNKOWN elements.

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