Product Selection Based on Upper Confidence Bound MOEA/D-DRA for Testing Software Product Lines

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Motivation:

- The product selection has been efficiently solved in the literature through search based techniques.
- However, it is not an easy task to configure parameters and operators of these algorithms.
- The use of Adaptive Operator Selection (AOS) solve this problem by adaptively selecting operators while the algorithm is in progress.

Goal:

- Evaluating several AOS methods for the SPL testing problem.
- Comparing the results to MOEA/D-DRA without AOS method, and with a random selection method.

Agenda

- Problem
- MOEA/D (Multiobjective Evolutionary Algorithm based on Decomposition)
- Adaptive Operator Selection
- Empirical Evaluation
- Results and Analysis
- Conclusions and Future Works

Problem

- Features are functionalities of the system which are visible to the user.
- Software Product Line (SPL) is defined as a set of products that share common features.
- A Feature Model (FM) represents all SPL variabilities and commonalities in terms of “features”.
- The FM is used to derive products for the SPL testing.
- The number of products (test cases) that can be derived from the FM grows exponentially with the number of features.
- It is necessary to select only the most interesting ones.

Problem

- Solving the product selection for Variability Testing of Feature Models by applying Pairwise and Mutation Testing.
- Binary encoding that represents a set of selected products (set of test cases).
- Multiobjective approach:
    - Minimizing the number of selected products.
    - Minimizing the number of alive mutants.
    - Minimizing the uncovered pairs of features.

MOEA/D

MOEA/D: Multiobjective Evolutionary Algorithm based on Decomposition.

It decomposes a Multiobjective Optimization Problem into sub-problems;

Each sub-problem is simultaneously optimized using information from neighboring sub-problems;

The MOEA/D-DRA algorithm used a Dynamical Resource Allocation that allocates more computational resources to the most promising sub-problems.

Adaptive Operator Selection

In this work, this algorithm dynamically selects the operators using Adaptive Operator Selection.

AOS is a recent paradigm that explores the dilemma “Exploration versus Exploitation”.

Best Operator x Not used Operator

Main concepts: Credit Assignment and Operator Selection.

Adaptive Operator Selection

Credit Assignment:

- Analyzing the recent performance of an operator to define its reward.
- A reward is quality measurement that verifies how good is the application of a particular operator.

Operator selection:

- Using the reward information of the operators to decide which operator should be applied.

Bandit-based AOS

Multi-armed bandit problem have been the focus of several studies by the Statistical community and offers a very clean and simple theoretical formulation, for analyzing the exploration and exploitation (EvE) dilemma.

Multi-armed Bandit

- The player can be seen as a gambler whose goal is to collect as much money as possible by pulling the arms over several turns.
- Bandit algorithms specify a strategy to determine which arm should be selected by the player on each turn.
- Many efficient ways to solve the MAB problem were proposed in literature.
- The Upper Confidence Bound (UCB1) algorithm is a method that ensures asymptotic optimality in terms of cumulative regret.

Multi-armed Bandit Selection

An UCB1 strategy is based on two components:

- The first component $q_{h,t}$ represents the quality of the $h_{\text{-th}}$ heuristic;
- The second gives an upper confidence bound based on the number of times $n_{h,t}$ that the heuristic was selected.

$$h(t) = argmax_{h=1..K}\left(q_{h,t} + \sqrt{\frac{2log\sum_k n_{k,t}}{n_{h,t}}}\right)$$

Operator Selection

Three MAB models are used to select the operators:

- UCB1 (called only UCB).
- UCB-V.
- UCB-Tuned.

The UCB-Tuned and UCB-V are similar to UCB,

Confidence intervals are utilized based on the variance of the operator qualities.

Credit Assignment

$$FIR_{op,t} = \frac{pf_{op,t} - cf_{op,t}}{pf_{op,t}} = \frac{g^{te}(x^i|\lambda^i, z^*) - g^{te}(y|\lambda^i, z^*)}{g^{te}(x^i|\lambda^i, z^*)}$$

Reward is computed as the sum of all FIR in a sliding window

All rewards are normalized resulting in FRRop (Fitness-Rate-Rank) rewards that are used by the operator selection procedure.

Operator Selection

Algorithm 1 Pseudocode of MAB Based Operator Selection

if There are operators that have not been selected **then**
  Randomly choose an unselected operator
else
  if MAB_Method == UCB **then**
    SelectedOperator = $argmax_{op=1..K}\left(FRR_{op} + C\sqrt{\frac{2ln\sum_{i=1}^{K} n_i}{n_{op}}}\right)$
  end if
  if MAB_Method == UCB-Tuned **then**
    for (**do**i = 0 to K)
      $V_{op} = \sigma_{op}^2 + \sqrt{\frac{2ln\sum_{i=1}^{K} n_i}{n_{op}}}$
    end for
    SelectedOperator =
    $argmax_{op=1..K}\left(FRR_{op} + C\sqrt{\frac{ln\sum_{i=1}^{K} n_i}{n_{op}} min(\frac{1}{4}, V_{op})}\right)$
  end if
  if MAB_Method == UCB-V **then**
    SelectedOperator =
    $argmax_{op=1..K}\left(FRR_{op} + C\sqrt{\frac{2ln\sum_{i=1}^{K} n_i\sigma_{op}^2}{n_{op}}} + 3\frac{\sum_{i=1}^{K} n_i}{n_{op}}\right)$
  end if
end if

Operators

Twelve operators were used.

Each operator selected consists in a combination among a crossover and mutation operator.

These operators are usually used in the literature.

	No Mutation	Bit Flip	One Change	Swap
Single Point	h1	h2	h3	h4
Two Points	h5	h6	h7	h8
Uniform	h9	h10	h11	h12

Algorithms Used

This work uses three algorithms based on MAB models:

- MOEA/D-UCB1
- MOEA/D-UCB-V
- MOEA/D-UCB-Tuned

In both, the MAB models were incorporated within MOEA/D-DRA algorithm.

When the algorithm applies an operator, this one was selected based on the MAB model.

Empirical Evaluation

Research Questions

RQ1: What is the best UCB-based selection method for this problem?

RQ2: Can the UCB-based algorithm generate better results than MOEA/D-DRA?

RQ3: Is there performance difference among UCB-based and random operator selection methods?

Feature Models Used

Four Feature Models (FM) were used in the experiments.

The greater the number of products, the more difficult the instance (FMs).

Instance	Products	Alive Mutants	Features	Valid Pairwises
JAMES	68	106	14	182
CAS	450	227	21	420
Weather Station	504	357	22	462
E-Shop	1152	394	22	462

Results and Analysis

RQ1: What is the best UCB-based selection method for this problem?

Hypervolume values

Instance	MOEA/D-UCB	MOEA/D-UCB-Tuned	MOEA/D-UCB-V	p-value
JAMES	0.96333 (0.00032)	**0.96343 (0.00027)**	0.96341 (0.00030)	0.15870
CAS	0.99274 (0.00029)	**0.99276 (0.00018)**	0.99276 (0.00022)	0.90210
Weather Station	0.98966 (0.00064)	**0.98968 (0.00057)**	0.98962 (0.00064)	0.74460
E-Shop	0.99576 (0.00056)	**0.99584 (0.00050)**	0.99566 (0.00066)	0.70170

Results and Analysis

Analysis

- The operator selection method does not influence on the solution and anyone can be chosen.
- The traditional MOEA/D-UCB was chosen. Its execution time was slightly better than the other algorithms.

Results and Analysis

RQ2: Can the UCB-based algorithm generate better results than MOEA/D-DRA?

Hypervolume for MOEA/D-UCB and MOA/D-DRA

Instance	MOEA/D-UCB	MOEA/D-DRA	p-value
JAMES	**0.96329 (0.00035)**	0.96322 (3.4E-4)	0.0712
CAS	**0.99277 (0.00020)**	0.99048 (0.00086)	< 2.2E-16
Weather Station	**0.99001 (0.00044)**	0.98585 (0.00139)	< 2.2E-16
E-Shop	**0.99602 (0.00042)**	0.97411 (0.00128)	< 2.2E-16

Number of solutions in PFKnown and PFApprox for MOEA/D-UCB and MOA/D-DRA

Instance	MOEA/D-UCB	MOEA/D-DRA
JAMES	10 (10)	10 (10)
CAS	36 (36)	16 (1)
Weather Station	35 (35)	16 (1)
E-Shop	27 (27)	3 (0)

Results and Analysis

Analysis

- The MOEA/D-UCB algorithm outperforms the MOEA/D-DRA one.
- The difference among them is more visible when the number of products to select increases (E-Shop).
- Advantage: to reach the best results, the tester does not need to select the best parameters for crossover and mutation operators.

Results and Analysis

RQ3: Is there performance difference among UCB-based and random operator selection method?

Hypervolume for MOEA/D-UCB and random operator selection method

Instance	MOEA/D-UCB	MOEA/D-RAND	p-value
JAMES	0.96327 (0.00033)	**0.96331 (0.00034)**	0.9882
CAS	0.99276 (0.00021)	**0.99279 (0.00020)**	0.4853
Weather Station	**0.98985 (0.00039)**	0.98974 (0.00038)	0.3280
E-Shop	**0.99596 (0.00048)**	0.99568 (0.00064)	0.0685

Number of solutions in PFKnown and PFApprox for MOEA/D-UCB and random operator selection method

Instance	MOEA/D-UCB	MOEA/D-RAND
JAMES	10 (10)	10 (10)
CAS	27 (19)	22 (17)
Weather Station	27 (21)	31 (17)
E-Shop	20 (17)	22 (8)

Results and Analysis

Analysis

- The UCB algorithm obtained similar performance to the random selection method.
- The results show a statistical equivalence.
- It is possible to conclude that the random operator selection method can be sufficient to reach good results.

Conclusions and Future Work

Conclusions

- This work investigates the use of MOEA/D with three UCB-based algorithms to derive products for SPL testing.
- All the UCB-methods presented similar behavior.
- MOEA/D-UCB outperformed the original MOEA/D-DRA.
- MOEA/D-UCB and random operator selection method has similar performance.
- For this problem, the use of a set of operators is enough to reach good solutions.

Future Works

Compare with others MOEAs and AOS methods.

Apply others operators.

New experiments with larger SPLs.

More objectives.

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Thank you!