

Integration Test of Classes and Aspects with a Multi-Evolutionary and Coupling-Based Approach

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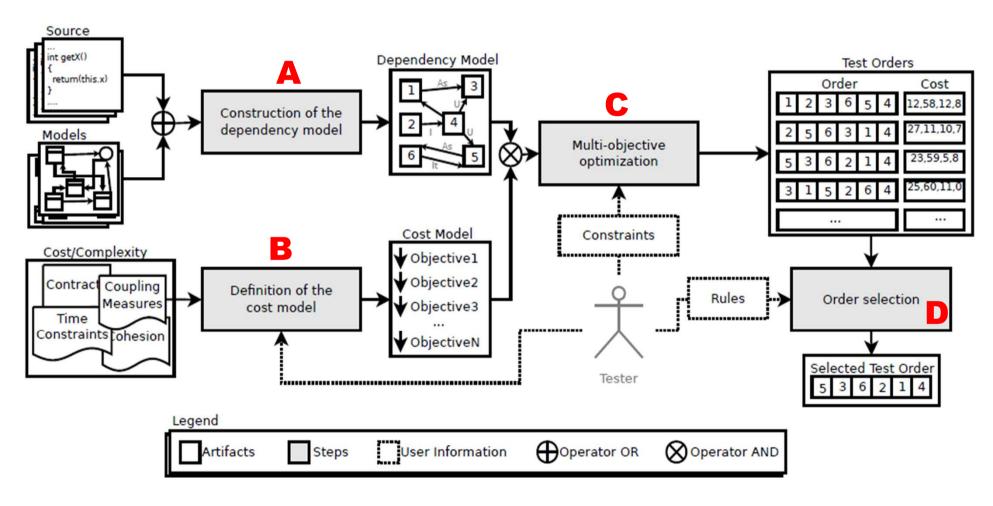
Introduction

- To determine a sequence for integration and test of classes and aspects that minimizes stubbing efforts
 - CAITO (Class and Aspect Integration and Test Order) problem
- Multi-objective evolutionary algorithms (MOEAs) have achieved better results than approaches based on graphs and genetic algorithms in CAITO/CITO contexts
 - They obtain a set of non-dominated solutions to approximate the Pareto front in a single run of the algorithm

Objectives

- To introduce MECBA (Multi-Evolutionary and Coupling-Based Approach) to solve the integration and test order problem
 - Generic steps for:
 - Definition of both dependency and cost models
 - Optimization through multi-objective algorithms
 - Output: set of solutions to integrate and test modules of a software
- MECBA was instantiated and evaluated in aspect-oriented context, with four AspectJ programs and four coupling measures
- Do MOEAs deteriorate their performance to the CAITO problem with more than two objectives?
 - The results of MOEAs were evaluated using four quality indicators and statistical test

MECBA (Multi-Evolutionary and Coupling-Based Approach)



MECBA

A – Construction of the dependency model

- Representation of the dependency relations to be considered
- Different restrictions to some kind of dependency can also be represented
- The dependency model adopted in our evaluation is the extended ORD [24] with the Combined strategy, in which classes and aspects are tested together

MECBA B – Definition of the cost model

- Coupling, cohesion and time constraints can be used
- Objectives to be minimized = 4 coupling measures
- m_i and m_j are two coupled modules and m_i depends on m_j Operation = class methods, aspect methods and aspect advices

Coupling measures:

- Attribute Coupling (A) = The number of attributes locally declared in m_j when references or pointers to instances of m_j appear in the argument list of some operations in m_i [3]
- Operation Coupling (O) = The number of operations locally declared in m_i, which are invoked by operations of m_i [3]

[3] L. C. Briand, J. Feng, and Y. Labiche. Using genetic algorithms and coupling measures to devise optimal integration test orders. In 14th SEKE, Ischia, Italy, July 2002.

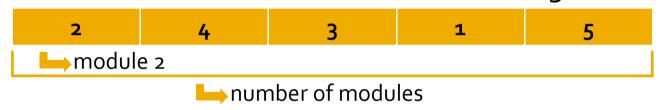
MECBA B – Definition of the cost model

- Coupling Measures:
 - Number of distinct return types (R) = Number of distinct return types of the operations locally declared in m_j that are called by operations of m_i [1]
 - Number of distinct parameter types (P) = Number of distinct parameter types of the operations locally declared in m_j that are called by operations of m_i [1]

MECBA C - Multi-Objective Optimization

Problem Representation

Permutation of modules which form testing orders



Fitness Function

- 1 matrix with dependencies between modules
- 4 coupling matrices (one for each coupling measure)
- Constraints: Inheritance and Inter-types dependencies cannot be broken
- Fitness of each solution: the sum of dependencies between modules for each coupling measure corresponds to an objective

MECBA C - Multi-Objective Optimization

Selection of a MOEA

- NSGA-II (Non-dominated Sorting Genetic Algorithm)
- SPEA2 (Strength Pareto Evolutionary Algorithm)

MECBA D – Order Selection

- The tester selects an order from the Pareto front of non-dominated solutions produced by the algorithms.
- This selection should be based on restrictions and priorities related to the software development, such as test goals, available resources, contractual restrictions, etc.

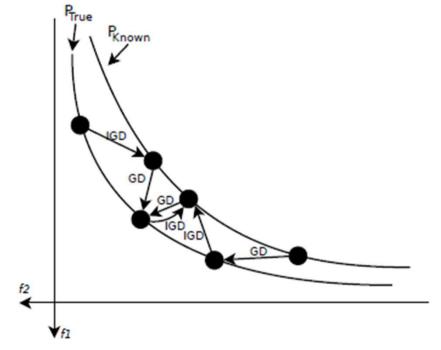
AspectJ systems

Software	Classes	Aspects	Dependencies	LOC
AJHotDraw	290	31	1592	18586
AJHSQLDB	276	25	1338	68550
Health Watcher	95	22	399	5479
Toll System	53	24	188	2496

- Parameters
- 30 runs

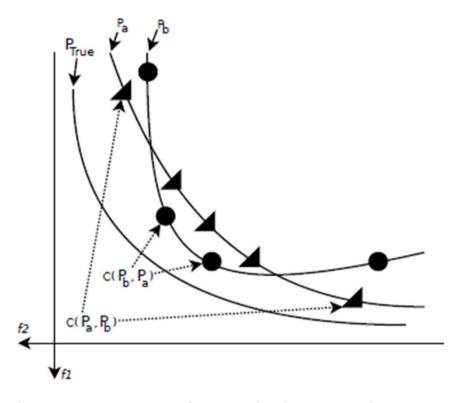
Quality Indicators

- Generational Distance (GD): calculates the distance from a PFApprox (Pknown) found to the Pareto Front (PFtrue)
- Inverted Generational Distance (IGD): calculates the distance from PFtrue to a PFApprox found



Quality Indicators

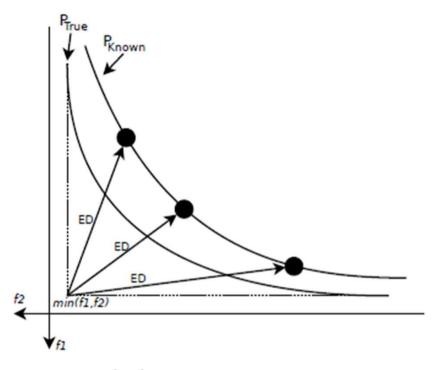
 Coverage (C): measures the dominance between two sets of solutions



The results of GD, IGD and C were analyzed through Wilcoxon test, in order to verify if NSGA-II and SPEA2 are considered statistically equivalent.

Quality Indicators

 Euclidean Distance from an ideal solution (ED): is used to find the closest solution to the best objectives

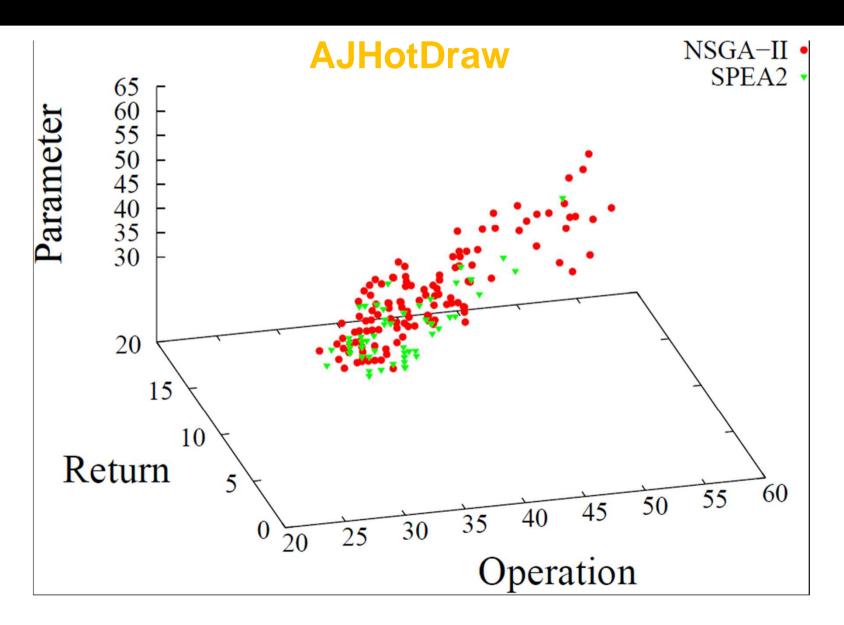


- Some of these quality indicators need the PFtrue, however, in real problems it is not known.
- It is common to use the non-dominated solutions found by all algorithms in all runs.

System	Dependencies	PFtrue Cardinality	MOEA	Total of Different Solutions of PFApprox
AJHotDraw	1592	95	NSGA-II	120
			SPEA ₂	51
AJHSQLDB	1338	105	NSGA-II	153
			SPEA ₂	40
Health Watcher	399	1	NSGA-II	1
			SPEA ₂	1
TollSystem	TollSystem 188 1	1	NSGA-II	1
		SPEA ₂	1	

•Health Watcher: $(A = 0, O = 0, R = 0, P = 0) \rightarrow 8$ cycles

•Toll System: $(A = 12, O = 2, R = 0, P = 1) \rightarrow 1$ cycle



GD and IGD

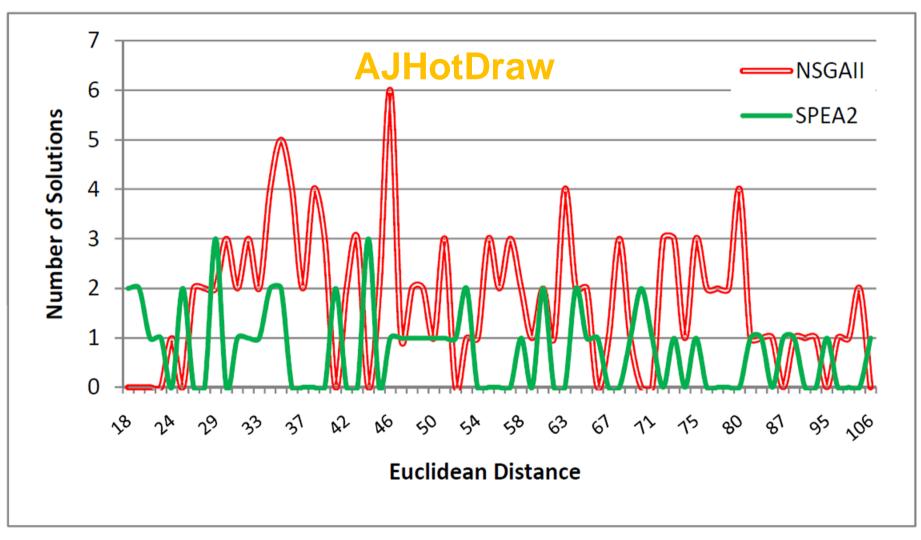
Indicator	System	Average of NSGA-II	Average of SPEA2
CD	AJHotDraw	0.0435	0.0560
GD	AJHSQLDB	0.0422	0.1075
IGD	AJHotDraw	0.0493	0.0380
	AJHSQLDB	0.0357	0.0641

Wilcoxon test points out that there is statistical difference between them for GD and IGD.

 Coverage: SPEA2 covers NSGA-II for AJHotDraw and AJHSQLDB, although without statistical significancy.

ED: SPEA2 achieved the lowest EDs.

System	Cost of the Ideal Solution	MOEA	Lowest ED	Fitness of the lowest ED
AJHotDraw	80, 24, 0, 31	NSGA-II	24.617	94, 37, 4, 46
		SPEA2	18.385	93, 28, 3, 43
AJHSQLDB	1877, 446, 189, 308	NSGA-II	205.842	2008, 569, 273, 363
		SPEA2	189.365	1960, 562, 26, 413
Health 0, 0, 0, 0 Watcher	0, 0, 0, 0	NSGA-II	0	0, 0, 0, 0
		SPEA2	0	0, 0, 0, 0
Toll System	12, 2, 0, 1	NSGA-II	0	12, 2, 0, 1
		SPEA2	0	12, 2, 0, 1



Discussion about the results

- NSGA-II and SPEA2 achieve feasible solutions despite exploring the solution space in different ways
- NSGA-II has the best distribution of solutions in the search space (great diversity of solutions) → better performance for GD and IGD
- SPEA2 has a good concentration of solutions near to the ideal solution → solutions of lower ED
- These solutions with lower ED cover some NSGA-II solutions improving the coverage rate of SPEA2 on NSGA-II
- Decision makers often prefer solutions near to the ideal solution → SPEA2 should be chosen

Selecting Orders

- How the tester should select a solution to integrate and test the modules of the system?
- Costs of solutions achieved by SPEA2 for AJHotDraw

	Α	0	R	Р	Ranking	Ideal Costs
а	87	49	11	52	18°	
b	111	24	1	43	14º	
С	102	29	0	44	7 °	(80, 24,0, 31)
d	184	43	14	31	51°	
е	93	28	3	43	1°	

Concluding Remarks

- MECBA was proposed and used for integration and test of classes and aspects
 - The dependency model considers specific characteristics of aspect-oriented programs
 - The cost model considers four coupling measures
 - NSGA-II and SPEA2 were evaluated
- It seems that SPEA2 is more appropriated to generate solutions that are closer to the ideal solution.
- MECBA can be efficiently used to solve the CAITO problem with four objectives
 - MOEAs found a set of different solutions containing different alternatives of compromise among the four objectives.
 - The tester can select the best solution according to the test priorities.

Future Works

- Perform other empirical studies:
 - to use a different strategy for integrate classes and aspects
 - with other aspect-oriented systems, and
 - to evaluate other MOEA and to analyze its behavior in the same context







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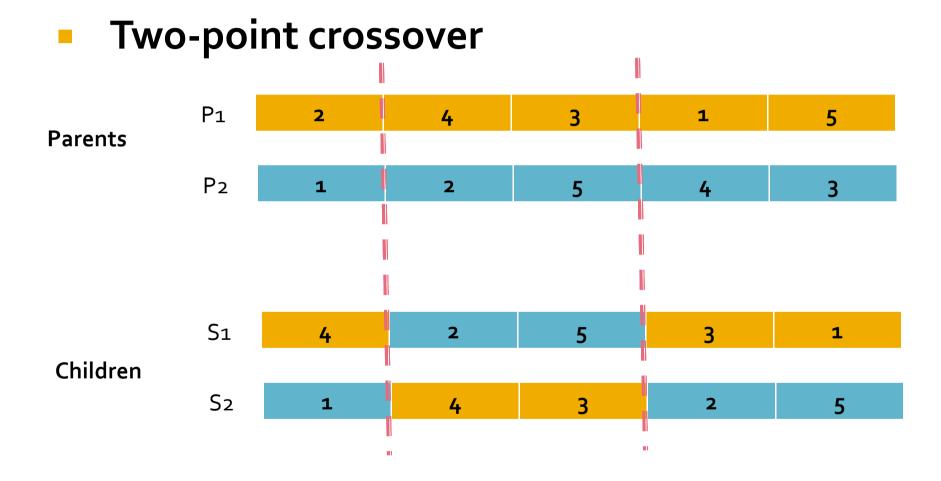


Multi-objective Evolutionary Algorithms (MOEAs)

- NSGA-II (Non-dominated Sorting Genetic Algorithm)
 - creates several fronts of individuals based on nondominance relation and discards solutions with lower dominance.
 - crowding distance operator ensures greater spread of solutions.
- SPEA2 (Strength Pareto Evolutionary Algorithm)
 - an external archive stores non-dominated solutions besides its regular population.
 - each solution has a strength value (fitness), which consists on the number of individuals dominated by this solution.

Parameter	NSGA-II	SPEA ₂
Population Size	300	300
Fitness Evaluation	20000	20000
Mutation Rate	0.02	0.02
Crossover Rate	0.95	0.95
Archive Size	-	250

Crossover operator



Matrices

Dependency Matrix

Class	Class Type of dependency	Class Type of dependency
1	2 It	31
2	4 As	
3	2 As	4 As
4	1 Us	3 As

Coupling Matrix – Measure A

Class	Class Measure A	Class Measure A
1	2 2	31
2	4 2	
3	24	4 2
4	1 2	3 5

