On the Performance of Multiple Objective Evolutionary Algorithms for Software Architecture Discovery

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Introduction

- **Search Based Software Engineering (SBSE)**
  - Apply metaheuristics to Software Engineering tasks
  - All stages of the software development

- **More specifically...**
  - Design phase
  - Architectural analysis
Introduction

- Software architectures are important design artefacts in the early software conception

- Software architects face to:
  - Multiple functional and, mainly, non functional requirements
  - A wide set of design decisions
  - Discovery of software structures and their interactions

- SBSE can support in design tasks: efficient search of architectural alternatives
Introduction

- **Multi-objective Evolutionary Algorithms**
  - Frequently applied in SBSE
  - Two or three objectives and classical algorithms (SPEA2, NSGA-II)

- **Many-objective Evolutionary Algorithms**
  - Rarely explored in problem domains like SBSE
  - Interesting alternative for high dimensional search spaces

- **Architecture Discovery as a multi/many objective optimization problem**
  - Comparative study of multi- and many-objective EAs
  - Scalability analysis: from 2 to 6 objectives
  - Different subsets of objectives related to software design
Evolutionary Discovery of Software Architectures

The software design problem

- Component-based software architectures in a nutshell:
  - **Component**: cohesive groups of classes
  - **Interface**: relationships between classes allocated in different components
  - **Connector**: pair of required and provided interfaces

- Focused on non-functional requirements

- Highly combinatorial problem
  - Different architectural styles
  - No prefixed structure
Evolutionary Discovery of Software Architectures

The search-based approach

**Phenotype**

**Genotype**

**Genetic operator**
- A roulette-based mutation operator to:
  - Add a component
  - Remove a component
  - Merge two components
  - Split a component
  - Move a class

**Initialization and constraints**
1. Randomly distribution of classes
   - No empty components and no replicated classes
2. Set interfaces and connectors
   - Isolated or mutually dependant components

SBSE @ GECCO 2014. Vancouver, Canada. July 15, 2014
Evolutionary Discovery of Software Architectures

The search-based approach

• The six objectives based on modularity and reusability

  - Intra-modular Coupling Density (ICD)
    
    \[
    ICD_i = \frac{Cl_i^{in}}{Cl_i^{in} + Cl_i^{out}} \quad ICD = \sum_{i=1}^{n} ICD_i
    \]

  - External Relations Penalty (ERP)
    
    \[
    ERP = \sum_{i=1}^{n} \sum_{j=1}^{n} \left[ w_{as} \cdot n_{ax_j} + w_{ag} \cdot n_{ag_j} + w_{co} \cdot n_{co_j} + w_{ge} \cdot n_{ge_j} \right]
    \]

  - Encapsulation (Enc)
    
    \[
    Enc_i = \frac{\#inner\ classes}{\#total\ classes} \quad Enc = \frac{1}{n} \sum_{i=1}^{n} Enc_i
    \]

  - Critical Size (CS)
    
    \[
    CC_i = \begin{cases} 
    1 & \text{if } size(i) > \text{threshold} \\
    0 & \text{otherwise}
    \end{cases} \quad CS = \sum_{i=1}^{n} CC_i
    \]

  - Instability (Ins)
    
    \[
    Ins_i = \frac{EC_i}{EC_i + AC_i} \quad Ins = \frac{1}{n} \sum_{i=1}^{n} Ins_i
    \]

  - Groups/Components Ratio (GCR)
    
    \[
    GCR = \frac{\#c\ groups}{\#components}
    \]
Evolutionary Discovery of Software Architectures

Multi- and many-objective evolutionary algorithms

SPEA2
- Generational algorithm
- Fitness = strength + density
- Binary tournament selection
- Archive with fixed size to store non dominated solutions

NSGA-II
- Non-dominated sorting
- Selection based on dominance and crowding distance
- Promotes the survival of non dominated solutions

ɛ-MOEA
- Steady state algorithm
- Landscape partition in hypercubes
- ɛ-dominance relation
- Archive of solutions

GrEA
- Inspired by NSGA-II
- Number of divisions as a parameter
- Grid-based metrics for crowding distance and spread of solutions

MOEA/D
- Decomposition approach
- A weight vector for each individual
- Neighborhood information
- Fitness based on a reference point
Experiments and results

- 6 diverse software designs
- All possible combinations of 2, 4 and 6 objectives per instance
- 30 runs
- Quality indicators:
  - Hypervolume (HV)
  - Spacing (S)
- Friedman and Holm’s statistical tests

Problem instances and set-up

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<tr>
<th>Common parameters</th>
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<tr>
<td>Population Size</td>
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<td>Max. Evaluations</td>
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<tr>
<td>Min-Max. Components</td>
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<tr>
<td>Mutator weights</td>
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<tr>
<td>ERP metric weights</td>
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<td>CS threshold</td>
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<table>
<thead>
<tr>
<th>SPEA2 parameters</th>
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<tr>
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<td>External population size</td>
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<table>
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<tr>
<th>$\epsilon$-MOEA parameters</th>
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<td>$\epsilon$ values</td>
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<td>$\epsilon_{CS} = 1, \epsilon_{Ins} = 0.05, \epsilon_{Enc} = 0.05$</td>
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<table>
<thead>
<tr>
<th>MOEA/D parameters</th>
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<td>Max. Replacements ($Nr$)</td>
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<td>$H$</td>
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<table>
<thead>
<tr>
<th>GrEA parameters</th>
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Experiments and results

From the perspective of the evolutionary performance

2 objectives

- Difficult trade-off between HV and S
- SPEA2 achieves good dispersion of the front
- NSGA-II, $\epsilon$-MOEA and GrEA usually outperform SPEA2 and MOEA/D in HV
- Poor performance of MOEA/D

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<th>NSGA-II</th>
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Algorithms perform similarly for some combinations of objectives (local and global optima)
### Experiments and results

From the perspective of the evolutionary performance

#### 4 objectives

- Multi-objective algorithms decrease their performance
- $\epsilon$-MOEA obtains the best rankings for both indicators

#### 6 objectives

- $\epsilon$-MOEA has significant differences with most of the algorithms (HV) and good spacing values
- SPEA2 maintains a substantial diversity

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Experiments and results

From the perspective of the decision-maker

- **SPEA2**
  - **Pros**: Variety of architectures (types and number)
  - **Cons**: Low quality solutions

- **NSGA-II**
  - **Pros**: Good scalability
  - **Cons**: Problems with complex instances

- **GrEA**
  - **Pros**: Trade-off between metrics
  - **Cons**: Strong tendency to certain types of solutions

- **MOEA/D**
  - **Pros**: Generates more non-dominated solutions
  - **Cons**: Diversity is not preserved in the external population

- **ε-MOEA**
  - **Pros**: Good trade-off between high quality and diversity
  - **Cons**: Low execution time and ability to remove invalid solutions
  - **Some problems with specific combinations of objectives**
Experiments and results

From the perspective of the decision-maker

- The selection of metrics has an important influence on the solutions found
  - Number of components comprising the architecture
  - Types of components and interactions

- The trade-off between design criteria
  - Instability and Encapsulation can reach good values in all the problems
  - ERP and GCR tend to complement each other well
  - Critical Size is usually demoted by other metrics
  - ICD is the most difficult metric to optimize
Concluding Remarks

• **Conclusions**
  - A first comparative study of multi- and many-objective evolutionary algorithms in Search-based Software Design
  - Different number and combinations of objectives: close to the reality
  - Strengths and weaknesses of each algorithm from the architect’s expectations

• **Future Work**
  - A more in-depth analysis of the most fitting algorithms for dealing with each specific set of architectural requirements
  - To extend the catalogue of metrics and used algorithms
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Thank you!