Evolutionary Mutation Testing Applied to Object-Oriented Systems

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Outline

Mutation Testing

A brief description

- Involves inserting simple syntactic changes in the program using **mutation operators**.
- This modification creates a new version called **mutant**.
- A non-detected mutant reveals a deficiency in our test suite.
- **Equivalence:** The change cannot be detected by any input.

Original program

```
if (x > 5) { ... }
```

Mutant: relational operator replaced

```
if (x < 5) { ... }
```

Test case	x = 5	x = 10
Original: $x > 5$	false	true
Mutant: $x < 5$	false	false
Classification:	Alive	Dead

Goals in Mutation Testing

Test suite evaluation

Measure how good is a test suite at detecting faults.

Test suite refinement

Improve the test suite to kill (detect) surviving mutants.

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Search for mutants inducing the design of new test cases.

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Phases in Mutation Testing

Four main phases:

1. Definition of mutation operators.

2. Development of a mutation framework

3. Evaluation of experimental results

4. Reducing the high cost of applying mutation testing.

Cost Reduction Techniques

Techniques "Do Fewer"

Reduce the number of mutants.

- *Mutant sampling.*
- *Selective mutation.*
- *High order mutation.*

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Recent technique

Evolutionary Mutation Testing

J. J. Domínguez- Jiménez, A. Estero-Botaro, I. Medina-Bulo and A. García-Domínguez
Evolutionary Mutation Testing
Information and Software Technology, 2011.
http://dx.doi.org/10.1016/j.infsof.2011.03.008

Evolutionary Mutation Testing

Evolutionary Mutation Testing *proposes the generation of a subset of the mutants by means of an* ***evolutionary algorithm****.*

This algorithm favors that the subset contains ***mutants with great potential to assist the tester in improving the test suite*** *with new test cases.*

Fitness Function

Execution matrix:

Operator	Mutant	Test cases: $test_1$	$test_2$	$test_3$
o_1	m_1	0	1	0
	m_2	1	0	0
	m_3	1	0	1
o_2	m_4	0	0	0
	m_5	0	0	1
	m_6	1	0	1

Fitness of mutants/individuals

- **Best valued (Strong mutants):**
  - **Potentially equivalent:** not killed by the current test suite.
  - **Resistant hard to kill:** killed by a single test case, which does not kill any other mutants.
- **Worst valued**: killed by many test cases, which in turn kill many other mutants.

Algorithm

Operator	Location	Attribute

Three fields are used to identify a mutant

- **Operator**: code representing the mutation operator.
- **Location**: order of location in the source file.
- **Attribute**: variant used in the location.

Original program

```
if (x > 0) {
   if (x > 5) {...}
```

Mutant

```
if (x > 0) {
   if (x < 5) {...}
```

- **Operator**: set of operators:
  - 1 (relational operator replaced)
  - 2 (arithmetic operator replaced)
- **Location**: possible locations: 1, 2
- **Attribute**: possible variants: >=, <=, <

MUTANT: 1 / 2 / 3

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MUTANT: 1 / 2 / 3

Algorithm

Individual generation

Individuals in a generation are:

1. **Randomly generated.**
2. **Generated by reproductive operators***:
   - **Mutation operators**.
   - **Crossover operators**.

* *Selection of individuals: roulette wheel method.*

Algorithm

Mutation operators:

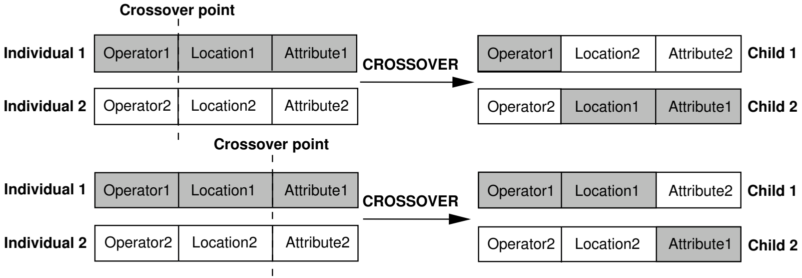
Operator	Location	Attribute

Algorithm

Mutation operators:

Operator	Location	Attribute

Crossover operators:



Research line

Motivation

- One of the most used programming languages [a].
- Search for cost reduction techniques.
- Evolutionary Mutation Testing had only been applied to WS-BPEL.

[a] 3rd position in the TIOBE index in June 2016

Goal

Is Evolutionary Mutation Testing useful in other contexts?

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Mutation operators

Class mutation operators

- Related to object-oriented features:
  - Inheritance
  - Polymorphism
  - Method overloading

Set of mutation operators

- The set of operators should be defined for each programming language:
  1. Common to other programming languages (Java and C#).
  2. Specific to the language.

P. Delgado-Pérez, I. Medina-Bulo, J. J. Domínguez-Jiménez, A. García-Domínguez and F. Palomo-Lozano.
Class mutation operators for C++ object-oriented systems
Annals of telecommunications, 2015.
http://dx.doi.org/10.1007/s12243-014-0445-4

Example

Example "Inheritance" block: IOD (Overriding method deletion)

Original:

```
class A {                          class B: public A{
    ... ...                            ... ...
    int method(){... ...};             int method(){... ...};
};                                 };
```

Mutant:

```
class A {                          class B: public A{
    ... ...                            ... ...
    int method(){... ...};             /*Deleted*/
};                                 };
```

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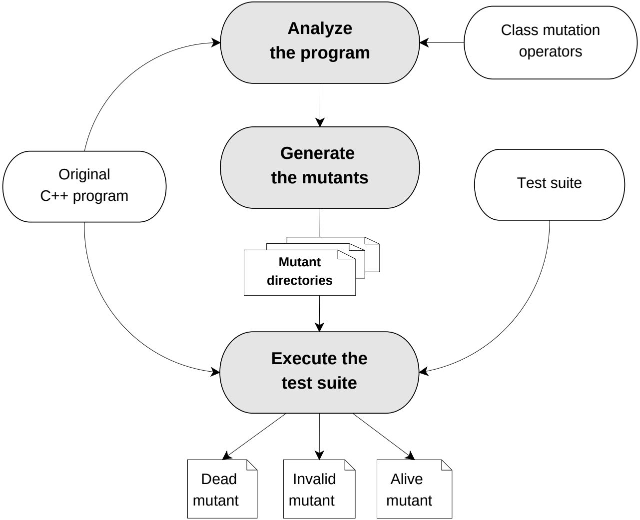
```

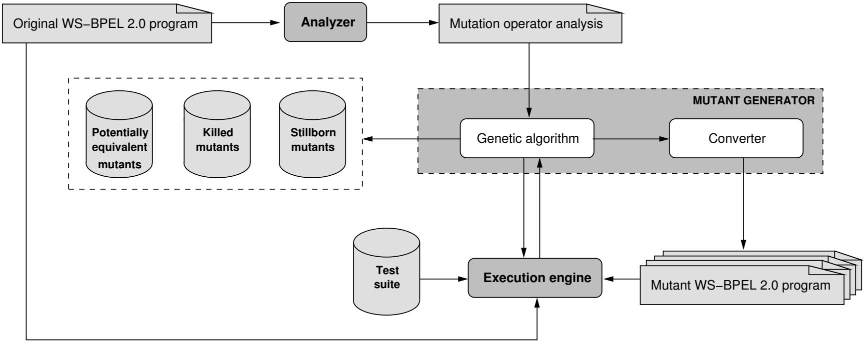
Main differences:

- Class operators are less prolific than traditional operators.
- High percentage of equivalence.

C++ mutation tool flow chart

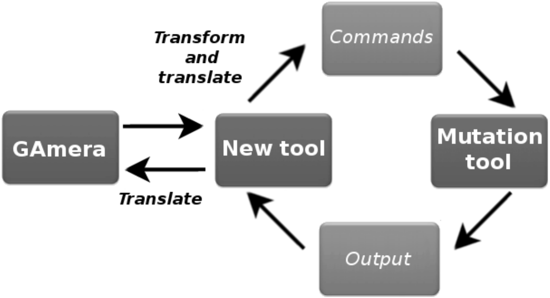


GAmera flow chart



*Its **modular architecture** allows to reuse the the genetic algorithm with different programming languages.*

GAmera / C++ mutation tool



Connection between applications

- Development of a **new application** to connect GAmera and the C++ mutation tool.
- **Tasks of this application**:
  - Transform GAmera execution commands into understandable commands for the mutation tool.
  - Translate the output between both applications.

Experiments

Evolutionary Mutation Testing VS Random Selection

1. **Random selection**: mutants selected one by one randomly.
2. **Evolutionary Mutation Testing**: generations are produced according to these parameters*:

• **Population size**:	5 %
• **New individuals randomly generated**:	10 %
• **New individuals generated by reproductive operators**:	90 %
• - Mutation probability:	30 %
• - Crossover probability:	70 %

* *These parameters were experimentally found as the best.*

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Termination

Stop condition: generation of a percentage of the total of **strong mutants**:

- 75 %
- 90 %

30 executions with different seeds.

Experiments

Case studies

- **Three programs** with different number of mutants and strong mutants*.
- We use the test suite distributed with the programs.

* *Strong mutants are known thanks to a previous execution.*

	Program 1	**Program 2**	**Program 3**	**Total**
Total mutants	219	614	1,146	1,979
Valid	208	433	681	1,322
Strong	103	159	348	610
% Strong mutants	49.5%	36.7%	51.1%	46.1%
Test cases	61	57	46	-

Experiments

Result 1

EMT outperforms Random in all the cases.

Result 2

The result is better with a low threshold (75 %).

Result 3

The efficiency does not scale with the number of mutants.

Result 4

The lower the percentage of strong mutants, the more efficient.

Threshold	*75%*		*90%*	
Technique	*EMT*	*Random*	*EMT*	*Random*
Program 1				
Mean	69.87	75.11	85.35	89.07
Median	70.09	75.79	85.38	89.72
MIN	62.55	67.57	78.99	82.64
Max	76.71	81.27	90.41	93.15
SD	3.57	3.57	2.67	2.86
Program 2				
Mean	64.91	74.93	84.32	89.98
Median	64.74	74.83	84.12	90.22
Min	60.58	69.70	77.85	85.01
Max	71.49	80.61	89.73	93.64
SD	2.59	2.78	3.34	1.78
Program 3				
Mean	69.96	74.43	87.84	89.76
Median	70.15	74.34	88.09	89.75
Min.	66.05	71.64	83.33	86.21
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Achievements

1. C++ mutation tool connected with the evolutionary algorithm.
2. Results confirms Evolutionary Mutation Testing as an efficient cost reduction technique.

Future work

- Confirm this tendency in new experiments.
- Introduce changes in the genetic algorithm.
- Check how this technique helps refine the test suite.

Summer School SBSE 2016

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