**A Technique for Generating Test Data using**

**Genetic Algorithms**

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**ABSTRACT**

Search-based testing techniques using genetic algorithm (GA) can automatically generate test data that achieve high coverage on almost any given test program. GA casts the path coverage problem as a search problem and applies efficient algorithms to find test data that can serve as suitable test cases. GA approaches have its strengths and weaknesses: it scales well and can handle any code and test criterion, but degrades when test program has any critical path clusters. This paper presents a method for optimizing GA efficiency by integrating a constraint solver to solve path conditions which GA cannot generate test data for coverage. The proposed approach is also applied some test programs. Experimental results show that improved GA which can generate suitable test data has higher path coverage than the standard GA.

**Categories and Subject Descriptors**

D.2.5 [**Software Engineering**]: Testing and Debugging – Testing Tools

**General Terms**

Algorithms, Reliability, Experimentation

**Keywords**

Genetic algorithm, path coverage testing, automatic test data generation

# INTRODUCTION

Software quality becomes more important than ever and software testing is the most significant measure for it. However, software testing is very laborious and costly due to the fact that it is mostly made by manual [1]. In general, software testing accounts for approximately 50 percent of the elapsed time and more than 50 percent of the total cost in software development [2]. Thus, automated software testing is a promising way to cut down time and cost.

Automatic structural test data generation is a crucial problem in software testing automation and its implementation cannot only significantly improve the effectiveness and efficiency but also reduce the high cost of software testing. We focus on path coverage test data generation in respect that various structural test data generation problem can be transformed into a path coverage test data generation problem. Furthermore, path coverage testing strategy can detect almost 65 percent of errors in test program [3].

Although path coverage test data generation is an undecidable problem [4], researchers still attempt to develop various methods and have made some progress. These methods can be classified into two types: static methods and dynamic methods.

Static methods include symbolic execution [5] and domain reduction [6, 7] etc. These methods suffer from a number of problems when it handles indefinite loops, array, procedure calls and pointer references [8].

Dynamic methods include random testing, local search approach [9], goal-oriented approach [10], chaining approach [11] and evolutionary approach [8, 12-14]. Since values of input variables are determined when programs execute, dynamic test data generation can avoid those problems with that static methods are confronted.

As a robust search method in complex spaces, genetic algorithm (GA) was applied to test data generation in 1992 [12] and evolutionary approach has been a burgeoning interest since then. Related works [8, 15, 16] indicate that GA-based test data generation outperforms other dynamic approaches e.g. random testing and local search.

As far as we know, even though GA-based test data generation already proved its efficiency in generating test data for dynamic approaches, it still has to face difficulties when the test program having test paths with low probability in generating coverable test data. For example, consider test program example1() as below [27]:

1 void example1(double x, double y, double z) {

2 if (Math.cos(z)- 0.95 < Math.exp(z)) {

3 if ((x + y == 1024) && (y > 1000))

4 // path 1

5 }

6 else

7 // path 2

8 }

By using constraint solvers, symbolic execution can generate test data for the second condition but not for the first. GA can solve the first condition. However, it has problems with the second condition. This mean that if only either symbolic execution or GA, we cannot have test data for the path 1.

This paper gives the proposal to improve GA in generating test data which can cover all the paths in the above test program. It combines constraint solvers into GA. The static program analysis step is applied to find out paths of the test program which are difficult to be covered. In this paper, the difficult path means the path contains if-else statements which is difficult to generate test data for coverage. For these difficult paths, the constraint solver Z3 [29] is used to generate the mutated individual. After that, mutated individual is used in the procedure of generating new populations in GA.

This paper is organized as follows: Section 2 gives some theoretical background to understanding this research. Section 3 summarizes some related works, and Section 4 presents the proposed approach in detail. Section 5 shows the experimental results and discussion. Section 6 concludes the paper

# BACKGROUND

This section describes to the some content is the theoretical background for the proposed approach of this paper.

## Path coverage test data generation as an optimization problem

To make use of genetic algorithm, a path coverage test data generation problem requires being transformed into an optimization problem.

Firstly, test program should be represented by its control flow graph (CFG). A CFG is a directed graph which can be denoted as G = (N, A, s, e) where N is a set of nodes, A is a set of edges; s and e are unique entry and unique exit node respectively. Each decision node is associated with a branch predicate, which is a logical expression. The edges leaving decision nodes are labeled with true or false values for corresponding branch predicate. To cause a path to be covered during execution, it is necessary to find appropriate values for the input variables that satisfy related branch predicates. A simple way is Korel’s branch distance function [9] based approach. For example, if a branch predicate C is (a == b), then the branch distance function f(C) = abs(a - b). So, to achieve a desired branch is transformed to search input vector that minimize its branch distance function. Table 1 gives some common used branch distance functions. To achieve a desired path P, we can define F(P) as the sum of all related branch distance functions. Consequently, generating path coverage test data can be transformed into searching input vector that can minimize F(P).

Table 1. Korel’s branch distance function

|  |  |  |
| --- | --- | --- |
| **No** | **Branch** | **Branch distance function** |
| 1 | a = b | f(C) = abs(a - b) |
| 2 | a ≠ b | f(C) = k |
| 3 | a < b | f(C) = (a - b) + k |
| 4 | a ≤ b | f(C) = (a - b) |
| 5 | a > b | f(C) = (b - a) + k |
| 6 | a ≥ b | f(C) = (b - a) |
| 7 | C1 ∧ C2 | f(C) = min(f(C1), f(C2)) |
| 8 | C1 ∨ C2 | f(C) = f(C1) + f(C2) |

In Korel function, k is the smallest step between 2 operands in the condition. In this paper, because all operand types are double, so to simplify we assume k = 0.

## Genetic algorithm

The basic concepts of genetic algorithm (GA) were developed by Holland [17]. GA is commonly applied to a variety of problems involving search and optimization. GA search methods are rooted in the mechanisms of evolution and natural genetics. GA draw inspiration from the natural search and selection processes leading to the survival of the fittest individuals. GA generates a sequence of populations by using a selection mechanism, and use crossover and mutation as search mechanisms.

The principle behind GA is that they create and maintain a population of individuals represented by chromosomes (essentially a character string analogous to the chromosomes appearing in DNA). These chromosomes are typically encoded solutions to a problem. The chromosomes then undergo a process of evolution according to rules of selection, crossover and mutation [28].

Each individual in the environment (represented by a chromosome) receives a measure of its fitness in the environment. Reproduction selects individuals with high fitness values in the population, and through crossover and mutation of such individuals, a new population is derived in which individuals may be even better fitted to their environment. The process of crossover involves two chromosomes swapping chunks of data (genetic information) and is analogous to the process of sexual reproduction. Mutation introduces slight changes into a small proportion of the population and is representative of an evolutionary step. The structure of a standard GA is given below.

1 Genetic Algorithm() {

2 initialize population;

3 evaluate population;

4 while (stopping criteria not reached){

5 select solutions for next population;

6 perform crossover and mutation;

7 evaluate population;

8 }

9 }

The algorithm will iterate until the population has evolved to form a solution to the problem, or until a maximum number of iterations have taken place (suggesting that a solution is not going to be found given the resources available).

## Conditional statements in Java

Java, like all other programming languages, is equipped with specific statements that allow us to check a condition and execute certain parts of code depending on whether the condition is true or false. Such statements are called conditional, and are a form of composite statement [26].

In Java, there are two forms of conditional statements:

* the if-else statement, to choose between two alternatives
* the switch statement, to choose between multiple alternatives

This paper will only focus to the if-else statement.

### The if-else statement

The if-else statement allows us to select between two alternatives.

Syntax:

if (condition)

then-statement

else

else-statement

### Condition in an if-else statement

The condition in an if-else statement can be an arbitrary expression of type Boolean. There are 4 types of if-else statement as below.

1. *a variable of type boolean*

Example:

boolean finished;

// ...

if (finished)

// ...

1. *one of the comparison operators (==, !=, >, <, >=, or <=) applied to variables (or expressions) of a primitive type*

Example:

int a, b, c;

// ...

if (a == b + c)

// ...

1. *a call to a predicate (i.e., a method that returns a value of type boolean)*

Example:

String answer;

// ...

if (answer.equalsIgnoreCase("YES"))

// ...

1. *a complex boolean expression, obtained by applying the boolean operators !, &&, and || to simpler expressions*

Example:

int a, b, c, d;

double e, f;

// ...

if ((a > (b+c)) || (a == d) && !(Math.abs(e-f) > 10))

In this paper we focus on 2 types of if-else statement, they are 2) (one of the comparison operators) and 4) (a complex boolean expression).

# RELATED WORK

The path coverage literature using GA started with Lin and Yeh [18] in 2000. They extended Jones et al.'s work [19] from branch coverage to path coverage. The ordinary (weighted) Hamming distance was extended to handle different ordering of target paths that have the same branches. The fitness function is called SIMILARITY, which computes similar items with respect to their ordering within two different paths between actual executed path and the target path. Only one program was used to test the approach, i.e. simple triangle classifier. They reported that the approach outperformed random search. However, in this method, test data generation must be called many many times in order to generate the test data for the most difficult path to be covered. In addition, because their work only used GA so the test program example1() in the section 1 cannot be covered all test paths.

Bueno et al. [20] proposed an approach that utilizes control and data flow dynamic information to achieve path coverage testing using GA. In addition, the work also tackled the detection of infeasible paths by monitoring the progress of evolutionary search. The fitness function was formulated by number of coincidence branches and the normalized branch predicate value at which the actual executed path starts to deviate from the target path. Six small test programs were used to validate the approach, with 10 repetitions each to minimize random variations. Two execution modes were used, i.e. one with initialized population and the other with a random initial population. The experiment results were promising.

In 2003, Hermadi and Ahmed [21] presented evolutionary test data generation for path testing using multiple paths. Prior to this work, almost all of the evolutionary test data generators only sought to cover a single target path at a time. The fitness function used the number of matching branches and branch predicate values using Korel's fitness function [9]. It also considered path traversal techniques, neighborhood influence, weighting, and normalization. Three small programs were used to validate the approach: minimum-maximum finder, triangle classifier, and a combination of both of them. Results were more effective and efficient by tackling multiple paths at a time.

In 2008, Ahmed and Hermadi [23] extended their work of 2003 [21]. The extensions were adding a rewarding scheme and using a more efficient test data generator. A total of 32 fitness function variations were tested empirically and analyzed to determine which the best was. There were 7 test programs used in the experiments. The results demonstrated that the approach was better compared to other existing work.

In the same year, Chen and Zhong [24] developed a multi-population genetic algorithm for path testing. This work has been improving GA-based path testing as described in Section 2.2. The work reported that the proposed approach outperformed a traditional genetic algorithm based approach, using the triangle classifier as the test program. Similar to our approach, this paper also targets finding the test data to cover path conditions of the most difficult path to be covered in test program. As it approached the parallel processing, test data generating time is better than standard GA, however the number of test data generation is still high (requires 21073 test data generation count by average).

In [25], Srivastava P.R and Kim T have presented a method for optimizing software testing efficiency by identifying the most critical path clusters in a program. The software under test is converted into a CFG. Weights are assigned to the edges of the CFG by applying 80-20 rule. 80 percentage of weight of incoming credit is given to loops and branches and the remaining 20 percentage of incoming credit is given to the edges in sequential path. The summation of weights along the edges comprising a path determines criticality of path. Higher the summation more critical is path and therefore must be tested before other paths. In this way by identifying most critical paths that must be tested first, testing efficiency is increased.

# PROPOSED APPROACH

This section describes details of our proposed approach for automatic test data generation using improved GA. In order to generate test data which can cover the paths having the lowest coverable probability, we propose 2 step approaches as in the above flow chart:



**Fig. 1. Flow chart of our proposed approach**

## Perform static program analysis

The purpose of this step to create a list of input parameters and their setting value by performing static analysis program and using constraint solver. We called this list by mutated individual list. This list is used as conditions of adjustment procedure for GA in the next step. To create this list we have taken the following steps:

### Solve path conditions

In this paper we analyzed two types of if-else statement Java language as discussed in section 2.3.2, there are "only one comparison operator" and "complex boolean expression". We also use constraint solver Z3 to solve these path conditions.

From experiments we found that, with the equal condition in the if-else statement, without any adjustments in GA, we cannot generate test data to satisfy these condition statements. Therefore, we extract equal condition from the if-else statement, solve them by using widely known constraint solver solve Z3 and stored constraint satisfaction (will be called mutated individual) in a list to adjust in GA.

### Store equal conditions

This paper uses below class to contain each mutated individual (output of constraint solver Z3) of a test program.

class Adjust

{

public int index; // index of input parameteri

public double value; // assigned value of parameteri

}

Back to the example1() test program mentioned in section 1, the second condition statement ((x + y == 1024) && (y > 1000)) (line 2) will be solved by constraint solver Z3 and stored in the list of class Adjust as below:

adjust[0].index = 0; // input parameter x

adjust[0].value = 23;// assigned value of x

// (constraint satisfaction from Z3)

adjust[1].index = 1; // input parameter y

adjust[1].value = 1001; // assigned value of y(constraint

// satisfaction from Z3)

## Execute GA

To automatically generate test cases, using GA with below procedures:

### Representation

Depend on the type of input parameters of test program, GA uses a double or integer vector as a chromosome *chrom* = (*x*1, *x*2… *xn*) to represent values of the input variables. The length of the vector depends on the required precision and the domain length for each input variable.

### Initial population

At first, it needs to identify a fixed *popsize* number is the number of chromosome in a population (called *popsize*) also maximum population generation for each time to run GA (called *maxgen*). Then initialize random values for all chromosomes in the first population.

### Fitness function

Korel’s branch distance function (mentioned in section 2.1) is used as fitness function in improved GA. To apply the Korel’s branch distance function we have to insert instrumented code into test program and use this test program as the fitness function of GA. For example, with test program example1() in section 1, instrumented code will be inserted into original code at line 2 and 9 as below:

1 double example1(double x, double y, double z) {

2 double ret = (Math.cos(z) - 0.95) - Math.exp(z);

3 if (Math.cos(z)- 0.95 < Math.exp(z)) {

4 if ((x + y == 1024) && (y > 1000))

5 // path 1

6 }

7 else

8 // path 2

9 return ret;

10 }

### Selection

A selection scheme is applied to determine how individuals are chosen for mating based on their fitness. Fitness can be defined as a capability of an individual to survive and reproduce in an environment. Selection generates the new population from the old one, thus starting a new generation. Each chromosome is evaluated in present generation to determine its fitness value. This fitness value is used to select the better chromosomes from the population for the next generation.

### Crossover and mutation

After selection, the crossover operation is applied to the selected chromosomes. It involves swapping of values of vector *x* = (*x*1, *x*2,…, *xn*) between two chromosomes. This process is repeated with different parent chromosomes until the next generation has enough chromosomes. After crossover, the mutation operator is applied to a randomly selected subset of the population. Mutation alters chromosomes in small ways to introduce new good traits. It is applied to bring diversity in the population.

### Adjustment

The purpose of the adjustment procedure is help GA can generate test data that can cover the entire test paths of the given test program. So that after executing the mutation based on list of mutated individual which are contained in list of Adjust class, we need to adjust the values of each chromosome in the population. The adjustment will be executed as follows:

void Adjustment(adjust list){

for each adjust[i] in the adjust list

chrom.x[adjust[i]] = adjust[i].value

}

# EXPERIMENTAL RESULTS

In this section presents the experimental results of test data generation of improved GA for 3 given test programs, and then compare results with standard GA.

## Programs under test

Also test program example1() presented in section 1, to demonstrate the effectiveness of our proposed approach, more than 2 test programs example2() and example3() are executed as follows:

### Example2 test program

This test program uses the Math library functions of the Java language, with the aim to determine whether the 3 input parameters of *x, y, z* can be shown for three sides of an isosceles right-angled triangle or not. Easy to see that the symbolic execution-based testing will not be applied to test this program, because there is no constraint solver can solve the Math library functions of the Java language in condition statement in line 2. Also standard GA has problem with condition statement in line 3.

1 void example2(double x, double y, double z) {

2 if ((Math.round(x) == Math.round(Math.hypot(y, z)))

3 && (y == z)) {

4 // path1

5 else

6 // path2

7 }

8 }

Our proposed approach is to perform static program analysis and determine the condition can solve by constraint solver Z3. Performing static program analysis obtains result in the condition (y == z) can be solve by constraint solver Z3 to get the constrain satisfaction (mutated individual) {y = 1, z = 1}. Two mutated individual will be transferred to the adjustment procedure of the improved GA.

### Example3 test program

Similarly example2(), 3 input parameters are the corner and two sides of a triangle. This program also uses the Math library functions of the Java language to determine if it is an equilateral, isosceles, scalene triangle or not. Symbolic execution-based testing cannot solve the condition statement in line 2 and 4, while standard GA also has problem with condition statement in line 3.

1 void example3(double corn,double edge1,double edge2) {

2 if (corn > 0 && corn < Math.PI) {

3 if (edge1 == edge2) {

4 if(Math.abs(Math.toDegrees(corn) - 60) < 0.01) {

5 // path1: Equilateral

6 }

7 else {

8 // path2: Isosceles

9 }

10 }

11 else {

12 // path3: Scalene

13 }

14 }

15 else {

16 // path4: Not a triangle

17 }

18 }

## GA parameters setting

Parameter settings of standard GA and improved GA are as following:

* Length of the chromosome: 3
* Selection method: random
* Two-point crossover probability (pc): 0.5
* Mutation probability (pm): 0.1
* Stopping criteria: all test target paths are covered

Each test program still requires other parameters below:

Table 2. GA parameter setting for each program

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Program** | **Type** | **Range** | **Max gen** | **Pop size** |
| example1 | double | [-10000,10000] | 150 | 250 |
| example2 | double | [0,10000] | 150 | 250 |
| example3 | double | [0,5] | 150 | 250 |

* Type: type of input variables
* Range: range of input variables
* Maxgen: maximum population generation for each time to run GA
* Popsize: number of chromosome for each population

## Results

The result test data generation of improved GA and standard GA is shown in the following tables. We will be evaluated according to two criteria: the number of test paths was covered and the number of times to perform test data generation.

### Test path coverage

This criterion will be evaluated based on the GA has a capacity to generate test data which can cover how many test paths of the given test programs.

Table 3. Test path coverage

|  |  |  |  |
| --- | --- | --- | --- |
| **Program** | **Feasible path** | **Standard GA** | **Improved GA** |
| example1 | 2 | 1 | 2 |
| example2 | 2 | 1 | 2 |
| example3 | 4 | 2 | 4 |

Table 3 shows that for 2 test programs (example2() and example3()), improved GA can generate test data for test path coverage is higher than standard GA.

### Test data generation counts

This evaluation criteria based on the number of times to perform test data generation which can cover the entire feasible paths in the given test program. In the case of generated test data cannot cover entire feasible paths, the test data generation count = *maxgen* x *popsize*.

Table 4. Test data generation counts

|  |  |  |  |
| --- | --- | --- | --- |
| **Program** | **Feasible path** | **Standard GA** | **Improved GA** |
| example1 | 2 | cannot cover all paths | 252 |
| example2 | 2 | cannot cover all paths | 9658 |
| example3 | 4 | cannot cover all paths | 1098 |

From Table 4, we can see that improved GA just uses limited test data generation to cover the entire data paths of the given test program, while the GA cannot do this.

# CONCLUSION

In software development life cycle, software testing is one of the critical phases. So generation of test data automatically is a key step which has a great influence on code coverage in software testing. In this paper, we have improved the GA in order to generate test data automatically for feasible execution paths.

Our proposed approach is from a given test program, we find out the condition that the GA will be difficult or impossible to generate coverage test data. Then we use the widely known constraint solver Z3 tool to solve this condition. The results obtained from the Z3 will be used again in the GA in procedures generate new populations.

The experimental results on these test programs shows that improved GA generated test data can cover all feasible paths having path conditions which cannot be covered by test data generated from standard GA.

Limitation of our proposed approach in this paper is applicable only constraint solver to solve only one path condition in the given test program. In the future we will expand the approach to solve many path conditions in a given test program.

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