A GENETIC ALGORITHM FOR REGRESSION TEST CASE PRIORITIZATION USING CODE COVERAGE

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Abstract— Regression testing is a testing technique which is used to validate the modified software. The regression test suite is typically large and needs an intelligent method to choose those test cases which will detect maximum or all faults at the earliest. Many existing prioritization techniques arrange the test cases on the basis of code coverage with respect to older version of the modified software. In this approach, a new Genetic Algorithm to prioritize the regression test suite is introduced that will prioritize test cases on the basis of complete code coverage. The genetic algorithm would also automate the process of test case prioritization. The results representing the effectiveness of algorithms are presented with the help of an Average Percentage of Code Covered (APCC) metric.

Keywords: Genetic Algorithm; Prioritization; Regression Testing; Automation Testing.

I. INTRODUCTION

Regression testing is retesting changed segments of application system. It is performed frequently to ensure the validity of the altered software. In most of the cases, time and cost constraint is prominent; hence the whole test suite cannot be run. Thus, prioritization of the test cases becomes essential. The priority criteria can be set accordingly e.g. to increase rate of fault detection, to achieve maximum code coverage, and so on.

One of the performance goals is to run those test cases that achieve total code coverage at the earliest [9]. Here, we propose a technique that achieves 100% code coverage. The three broad categories for prioritization are Greedy algorithms, non-evolutionary algorithms and evolutionary algorithms. Evolutionary algorithms (EA) have been chosen as they are global optimization methods and scale well to higher dimensional problems. They can be easily adjusted to the problem at hand and can be change and customized.

It is interactive and meta-heuristic process that operates on a set of population. Most of the implementations of evolutionary algorithms came from any of these three basic types: Genetic Algorithm (GA), Evolutionary Programming (EP) and Evolutionary Strategies (ES). All these are strongly related but independently developed. Among evolutionary techniques, the GA, invented by John Holland in the 1960s at the University of Michigan, study the phenomenon of evolution and adaptation as it occurs in nature. They depend on the use of selection, crossover (recombination) and mutation operators [9]. Automated software testing has been considered critical for big software development organizations but is often too expensive or difficult for smaller companies to implement. This algorithm automates the process of prioritize the test suites as per the criteria given to genetic algorithm.

II. RELATED WORK

Many researchers addressed prioritization problem and proposed various techniques for it. Many techniques are used for prioritization such as Greedy algorithms for test case prioritization [13], 2-optimal algorithms [7], non-evolutionary algorithms such as goal programming method [4], logarithmic least square method [5], weighted least square method [5] and evolutionary algorithms[3]. Most frequent among all is total fault-detection technique [15].

In the test case prioritization using genetic algorithms, the prioritization criterion is based on fitness function of population and genetic operators [11]. Further, Genetic algorithm is used for network security in cryptography [8]. GA is also used in Data Mining operations [12] and Robotics [14].

III. THE GENETIC ALGORITHM

Over several years, organisms are evolving on the basis of fundamental principle "survival of fittest" to accomplish noteworthy results. In 1975, Holland employed principle of natural evolution to optimization problems and built first GA.

In GA, a population $P = (c_1..., cm)$ is formed from a set of chromosomes and each chromosome is composed of genes. The GA populates the population of chromosomes by successively replacing one population with another based on fitness function assigned to each chromosome. The strong individual is included in next population and individuals with low-fitness are eliminated from each generation. [10]. There are two main concepts in genetic algorithm viz: crossover and mutation.

A. Crossover

The crossing over (key operator) is process of yielding recombination of alleles via exchange of segments between pairs of chromosomes. Crossover is applied on an individual by switching one of its allele with another allele from another individual in the population. The individuals resulting from crossover are very different from their initial parents. The code below suggests an implementation of individual using crossover:

Child1 = $c*parent1 + (1-c)*parent2$	(1)
Child2 = (1-c)*parent1 + c*parent2	(2)

B. Mutation

The mutation is a process wherein one allele of gene is randomly replaced by (or modified to) another to yield new structure .It alters an individual in the population. It can regenerate all or a single allele in the selected individual. To maintain integrity, operations must be secure or the type of information an allele holds should be taken into consideration. That is, mutation must be aware of binary operations, or it must be able to deal with missing values.

A simple piece of code: child = generateNewChild();

(3)

The optimization problems are solved by GA's recombination and replacement operators, where recombination is key operator and frequently used, whereas, replacement is optional and applied for solving optimization of problem.

IV. GENETIC ALGORITHM FOR PRIORITIZATION OF TEST CASES

The initial population is automatically generated and the evaluation of the set of candidate solution has been done with the help of genetic algorithm. The stopping criteria used in this approach is total code coverage.

A. Flowchart



Figure 1. Flowchart of Genetic Algorithm.

B. Algorithm

STEP 1. Generation of initial population Generate 'n' number of chromosomes {c₁, c₂... c_n}
STEP 2. Initialization of population Set Test Suite= No. of chromosomes (n)
STEP 3. Fitness function criterion set Set fitness function= total code coverage
STEP 4. Select suitable population on the basis of Fitness Function SELECT (Best 2 chromosomes based on fitness function)
STEP 5. Genetic Operators Applied Do for selected Chromosome(s) While (all conditions are covered) Do crossover Do mutation Remove Duplicacy EndWhile

EndFor

STEP 6. Optimization of solution cheked. If (solution!= feasible) Goto STEP 5 Else END.

C. Algorithm Explained:

In GA, the optimal solution is searched on the basis of desired population which further can be replaced with the new set of population. The generation and initialization of test cases (population) is done according to the problem. The two fitness criterion chosen are maximum fault covered in minimum execution time and total code coverage. Henceforth, this fitness function will help in selecting suitable population for problem. Further, the genetic operations are performed. Firstly, crossover, which recombines two individuals. Secondly, mutation, which randomly swaps the individuals. Thirdly, the redundant individuals are removed. Finally, the solution is checked for optimization. If solution is not optimized, then, the new population is reproduced and genetic operators are applied.

D. Problem Definition:

Prioritization based on total code coverage is done by structural testing. This is achieved through path testing which is a group of test techniques based on selecting a set of test paths through the program. Flow graph generation is the first step of path testing. Then decision to decision (DD) path graph is generated form flow graph. It is used to find independent paths. An independent path is any path through the DD path graph that introduces at least one new set of processing statements or new conditions. Therefore, we need to execute all independent paths at least once during path testing. The example is explained below:

The example taken for code coverage is the triangle problem which takes the three sides (a positive integer in the range of 0 to 100) of the triangle as input and gives the output as scalene, isosceles, equilateral, not a triangle and invalid inputs according to the input[11]. The test cases, conditions and independent paths covered by them are shown in the table 4.



Figure2. DD Path graph of Triangle problem.

Following are the independent paths of the triangle problem:

- i. ABFGNPQR
- ii. ABCDEGHJKMQR
- iii. ABCDEGHIMQR
- iv. ABCDEGNOQR
- v. ABCEGNPQR
- vi. ABCDEGHJLMQR
- vii. ABFGNOQR

INPUTS

Table I. Test cases with inputs and outputs

TEST	INDEPENDENT	CONDITION
CASE	РАТН	COVERED
NO.		
1	abfgnpqr	3
2	abcdeghjkmqr	5
3	abcdeghjkmqr	5
4	abcdeghimqr	4
5	abcdeghjkmqr	5
6	abcdegnoqr	4
7	abcegnpqr	4
8	abfgnpqr	3
9	abcdeghjlmqr	5
10	abcdeghjkmqr	5
11	abcdeghjkmqr	5
12	abcdeghjkmqr	5
13	abfgnoqr	3
14	abcegnpqr	4
15	abfgnpqr	3
16	abcdeghjkmqr	5
17	abcdeghjlmqr	5
18	abcdeghimqr	4
19	abcdegnoqr	4
20	abcegnpqr	4

Step 1: Test case Generation

We are applying the foremost step of our algorithm by selecting the randomized test suites. The number of test cases is the number of chromosomes generated. This is explained in the table 5 given below.

CHROMOSO		OBSERVATIONS FOR 1 st ITERATION										
C1	G	T1	Т5	T6	Tθ	Т4	Т7	T11	T17	T20		
C^2	G	T2	T/	Т0 Т9	T12	T16	T18	T7	T8	T10	T6	Т20
C2 C3	G	T2 T3	T15	T17	T12 T19	T6	T20	T/	T13	T5	T1/	120
<u>C4</u>	G	T4	T6	T17	T0	T12	T10	T20	T1 T1	T3	T14 T12	Т7
C4 C5	C	T5	10 T8	T17	T15	T12 T10	T10 T20	T14	T6	T11	T12 T10	T7
C5	C	15 T6	10 T12	T12	T10 T20	T16	T20	T14 T10	T0 T4	111	110	1/
C0	G	T0 T7	T0	T13	T120	T10 T14	12 T18	T19 T10	T20	T4		
C7	G	17 T8	T10	T14	T20	T14 T12	T10	T0	T20	T6	Т7	
	C	10 T0	T10	T14 T12	T20	T12	14 T5	T4	T10	T17	T20	
C10	G	15 T10	T12	T12 T14	10 T16	T10	T20	14 T6	T10 T2	T1/	T120	
C10	C	T10 T11	T12	114 T15	T10 T20	T10	120 T1	T10	12 T17	14 T2	T15	
	G	111	115	115	120	119	11	118	11/	15	14	
C12	G	T12	T14	T16	T18	T4	T20	T9	17			
C13	G	T13	T17	T20	T19	T6	T14	T12	T6	T7	T4	
C14	G	T14	T4	T19	T6	T8	T12	T5	T20	T3	T1	
C15	G	T15	T3	T7	T9	T4	T1	T18	T10	T14	T20	
C16	G	T16	T10	T19	T20	T5	T11	T8	T14	T4	T12	
C17	G	T17	T5	T1	T16	T7	T6	T17	T12	T20	T2	T4
C18	G	T18	T19	T15	T17	T5	T20	T8	T9	T2	T4	
C19	G	T19	T4	T13	T14	T3	T6	T1	T7	T3	T20	
C20	G	T20	T4	T1	T2	T8	T3	T18	T6	T9	T16	T19

Table II. Execution of Example, G-Genes, C- Chromosome

Step 2: Select an input for GA algorithm based on the fitness function

The fitness function in this is selecting minimum test cases to cover all the independents paths with minimum test cases. Two test suites of eight test cases and two test suites of nine test cases are selected as per the fitness function. The crossover is applied on test suites of similar length. The 3-point crossover is applied on two sets of test suites.

Two offsprings are formed on applying crossover. One of the two offspring covers all the independent paths while the other does not cover all the independent paths and hence that offspring is discarded.

Thus based on this fitness function, we get two iterations with test suite {T6,T12,T1,T20,T16,T2, T19 and T4} and {T12,T14,T16,T18,T4,T20,T9,and T7}.

Step 3: Apply Genetic Algorithm on test suite of nine test cases does not yield optimized result. Thus, we apply on test suite of eight test cases to further prioritize.

Step 3.1. Do crossover



Figure 3. Applying crossover on the test suite

Thus the test suites we get after crossover as two offsprings are

т6	т12	Т1	T19	т4	T20	то	Т7
10	112	11	110	14	120	17	1/

And

T12	T14	T16	T20	T16	T2	T19	T4

The first offspring i.e. test suite obtained after crossover covers all the independent paths and that test suite is selected for mutation. The test suite selected is as:

T6	T12	T1	T18	T4	T20	Т9	T7

Step 3.2 Do mutation on one of the best offspring and the process shown is as:



Figure 4. Applying mutation on the resulted test suite

The result obtained after applying mutation is

T6 T7 T	Т9	T4 T2	0 T18	T12
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Step 3.3 removing the duplicates from the test suites

Thus, removing the duplicate test cases T18 and T12, we get the final test suite which covers all the seven independent paths as below and this is the final result.

T6	T7	T1	T9	T4	T20
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E. Algorithm Analysis:

To analyze code coverage based testing effectively the Average Percentage of Condition Coverage (APCC)[16] approach has been used where average percentage of test suite to be executed with respect to average condition's covered.Table-9 shows various orders for Example-3 and corresponding APCC is plotted in figure 9. In this paper, Example-3has used APCC. The APCC is given as:

$$APCC = \frac{1 - 7C1 + 7C2 + \dots + 7Cm}{nm} + \frac{1}{2n}$$

Where, T = test suite been executed n = number of test cases, m = number of conditions to be covered, TC_i = First test case covering ith condition.

Table III shows the final percentage calculated from APCC for example. Table IV shows proposed technique is comparable with optimum order for the examples.

(4)

Technique	Example
	APCC %
No Order	90
Random Order	89.2
Reverse Order	89.2
Optimal Order	91.7
GA Order	88.3

Table III. Representing APFD and APCC values.

Table IV. Order of test cases for various prioritization approaches for example of maximum code coverage.

No	Reverse	Random	Optimum	GA
Order	Order	Order	Order	Order
T1	T20	Тб	Т9	T6
T2	T19	T8	T7	T8
T3	T18	T10	T4	T10
T4	T17	T5	T2	T2
T5	T16	T4	T18	T20
T6	T15	T2	T1	T15
T7	T14	T1	T13	T13
T8	T13	T9	T3	Т9
Т9	T12	T7	T5	T7
T10	T11	T3	T8	T1
T11	T10	T16	T6	T3
T12	T9	T13	T10	T12
T13	T8	T19	T19	T16
T14	T7	T20	T11	T14
T15	T6	T17	T15	T11
T16	T5	T19	T12	T17
T17	T4	T12	T16	T19
T18	T3	T18	T14	T5
T19	T2	T11	T17	T18
T20	T1	T14	T20	T4



Figure 5. APCC chart for example 1 of maximum code coverage.

F. Threats to Validity:

The GA algorithm proposed here has been executed and following areas have been detected as threat to validity.

- 1. The optimal result depends on observing the final result.
- 2. The algorithm has been tested on less number of programs. More analysis is needed.

V. APPLICATION OF THE PROPOSED APPROACH

This approach may be used by the software practitioners to reduce the time and effort required for prioritization of test cases in the test suite. The proposed approach may lead to greater savings of time and effort in larger and

complex projects as compared to smaller ones. Using GA approach, software practitioners can effectively select & prioritize test cases from a test suite, with minimum execution time. Hence, the proposed algorithm may prove to be useful in real-life situations.

VI. CONCLUSION

The algorithm has been proposed to prioritize test cases using Genetic Algorithm. Here, different prioritization approaches have been analyzed, namely: total fault coverage with in time constrained environment and amount of code coverage on different examples and their finite solution obtained, respectively. Through Genetic Algorithm technique, an approach has been identified to pull out suitable population, which was further formulated by GA operations to make it more flexible and efficient. The elaborations of results are shown with the help of APCC values. The APCC has been calculated for example for code coverage testing to evaluate the usefulness of the proposed algorithm.

The algorithm is solved manually and is a step towards Test Automation. In future an automation tool is to be developed to implement the proposed algorithm which can solve large number of test cases in efficient time.

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