An Approach for Domain Reduction with Data Dependence in Mutation Testing

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Abstract—As a testing strategy to evaluate the completeness of test cases, mutation testing has been identified as a "fault-oriented" technique for unit testing, which is mainly used to generate complete test cases. The path-oriented technique of test data generation is a highly efficient technique which implements test data generation by building and solving constraint systems. Most of path-oriented generation techniques only take control dependence among statements into consideration, which is to build constraint system by analyzing control flow graph. However, it neglects the influence of data dependence among statements on constraint system. Therefore, this paper improved test data generation technique of domain reduction and proposed a new domain reduction method with data dependence. It added detecting of equivalent mutants and solved influences on constraint systems caused by multiple conditional branch statement. Experimental results showed that this method improved success rate and execution efficiency of test data generation in a significant extent.

Index Terms—Mutation testing, Equivalent mutant, Constraint system, Automatically software testing, Test data generation

I. INTRODUCTION

Mutation testing is a kind of "fault-oriented" technique for unit testing [1,2]. Mutation testing is based on two basic hypotheses [1,3]: (1) Coupling effect hypothesis. (2) Competent programmer assumption. Based on this assumption, mutation testing uses mutation operator [4-7] to syntactically change a simple test program statement, and automatically generates sets of error procedures corresponding to original program which were known as mutants. When we Use existing test cases in mutation testing, if mutants' output is different from original program's output or mutants stop running before the end of program, the mutants can be killed by test cases, then reselect the other live mutants to do the same operation until all mutants are killed or attain a certain mutation score [4].

For a program \( P \) and a set of test data \( T \), the number of mutants is \( M \), the number of dead mutants is \( D \), and the number of equivalent mutants is \( E \). The mutation score is defined to be:

\[
MS(P, T) = \frac{D}{M - E}.
\]

\( P \) is a program, \( M \) is a mutant of \( P \) on statement \( S \), and \( t \) is a test case for \( P \). If \( M \) can be killed by the test case \( t \), we call \( t \) is valid, otherwise \( t \) is invalid. To kill \( M \), \( t \) needs three broad characteristics [15,25]: (1) Reachability; (2) Necessity; (3)Sufficiency. Sufficiency will not be considered in this paper.

There are three main reasons for the mutants not to be killed: (1) The set of test cases is not complete enough, and need to generate new test data to kill the mutants; (2) The mutants are functionally equivalent to the original program, viz, equivalent mutant. The equivalent mutant accounted for about 10% of the total number of mutants [8,9]; (3) Data values of mutant statement is shielded or application of software error correction technology lead to the fact that the mutants can't be killed, and it is an undecidable problem [10].

We have given a test data generation method in reference [11]. But this method did not consider the influence caused by equivalent mutant. If the mutant is equivalent mutant, the mutant cannot be killed. So we give a method to detect equivalent mutant in test data generation process. In addition, we solved the problem of the multiple conditional branch statement.

II. RELATED WORKS

TDG (Test Data Generation) is defined as selecting appropriate test standard and input process for identification which satisfies requirements [8]. TDG has been widely applied by industrial circles such as web applications testing [12], flight simulator fidelity evaluation [13], and etc. According to generate way, TDG can be divided into random, path-oriented, and goal-oriented test data generation [14]. Random TDG is a simple method, but random approach has low probability in finding semantically small faults. Path-oriented TDG includes constraint-based TDG (CBT) [4], dynamic domain reduction TDG (DDR) [15], and an improved method presented in reference [16]. Path-oriented
approach has better prediction of coverage, however, it is more difficult to find test data and it often selects infeasible paths. In these three path-oriented approaches, CBT is a highly effective TDG method. However, CBT can’t handle loop statements depending on input variables and array indexes. It is likely to cause a solvable constraint system to become unsolvable [15,16,18]. DDR introduces dynamic translations of control flow graph (CFG) to solve the problem of loop, arrays and pointers that CBT cannot handle. DDR is more effective than CBT in time and space aspect [15,16]. Reference [16] combines the CBT and DDR. It reduces the amount of TDG by assembling not contradictory necessity conditions in constraint system. It solves constraint system through iterative relaxation method [19]. Goal-oriented TDG includes chaining approach for TDG (CAT) [8], and assertion-oriented approach [8,17]. Goal-oriented approach is difficult to predict the range of the coverage but more flexible to find test data and reduce the probability of selection relatively infeasible paths. CAT considers describes both control flow and data flow as event sequence, it improved the testing data discovery rate. There are also many other optimize on TDG. Reference [20] proposes a micro-kernel engine to optimize the automatic test system and reference [21] proposes a software reliability test method based on Markov usage model. Many methods use the genetic algorithm to optimize the TDG [22,23,24]. Reference [25] proposed a reusing test cases method because half of the code of the software systems written today is to produce the required GUls.

III. CONSTRAINT-BASED MUTATION TESTING

Figure 1 is a sample program and the corresponding control flow graph. For example of Figure 1, a set of nodes is \( N = \{1, P1, P2, P2, 3, 4, 5, P3, P4, P5, P6, P7, 14, 15\} \), a set of edge in \( N \) is \( E = \{(1, P1), (P1, P2), (P2, P3), (3, 4), (4, 5), (5, P3), (P3, P4), (P4, P5), (P5, P6), (P6, P7), (P7, 14), (14, 15)\} \), unique entry is node 1, and unique exit is node 15. TDG is a sequence of node \( <N_i, N_j> \). For example the path we mentioned above can be expressed as \( \langle 1, P1, P2, 3, 4, 5, P3, P4, P5, P6, P7, 14, 15 \rangle \). A set of Input variables is \( I = \{a, b, c\} \). Input domain is \( D = D_a \times D_b \times D_c \). TDG is to find \( a \in D, b \in D, c \in D \) to execute the program. Branch predicate expression is \"a > b\". No transfer condition describes the transfer condition for each edge in G such as \( BP(P2, 3) = \"a > b\"\). A path in CFG from node 1 to node 14 is a sequence \( P = \langle P1, P2, P3, 3, 4, 5, P3, P4, P5, P6, P7, 14, 15 \rangle \). We mark \( P^* \) if \( P \) in loop statements. If there is a program input \( I \) traversed \( P \), we called \( P \) as feasible path, and otherwise \( P \) is infeasible path. Usage set of variables in node 4 as \( U(4) = \{a, b\} \). Definition set of variable in node 4 is \( D(4) = \{a\} \). Path \( P = \langle N_i, ..., N_j \rangle \) from node \( N_i \) to node \( N_j \) is a definition-clear path to partial set of variables \( S \). If \( S \) is not modified except for node \( N_i \) and node \( N_j \), and \( N_i \) dependent on node \( N_j \), we called node \( N_i \) and node \( N_j \) DU-Pair, node \( N_i \) is dependent on node \( N_j \).

Constraint-based TDG technology, including CBT, DDR and the method introduced in reference [16], has two key problems: (1) Constraint system building; i.e., building the constraint system by reachability condition and necessity condition; (2) Constraint system solving, which tells how to automatically generate test data. These three methods have better efficiency in execution, but they still have a shortage that the whole generation process is only guided by CFG. It has two influences because of its own information limitations: (1) Path-oriented TDG must generate a great deal of paths, and judge and choose them until a valid path is obtained, and it is fatal to complex system; (2) It could cause no solutions because of the difficulty of achieving the destination node if ignoring data dependence.

For improving goal-oriented and path-oriented methods, we combine the goal-oriented CAT method and present an approach for domain reduction with data dependence (DRD). It added the detecting of equivalent mutants and solved the problem of the multiple conditional branch statement. It uses the path with data dependence (PDD). The last variable definition set in node \( n \) is \( LD(P5) = \{4, 5, 7, 8, 10, 11\} \) in figure 1. The set of data dependence with node \( P5 \) for path \( P = \langle 1, P1, P2, 3, 4, 5, P3, P4, P5, P5, 12\rangle \), we get \( LDP(P5) = \{3, 4\} \). PDD is an extended representation of the path. It not only contains the control information of the path, but also data dependence information of all nodes. We marked the node \( n \) and the last variables definition set with \( n:LDP(n) \). PDD is a sequence of node \( n:LDP(n) \). For example the path we mentioned above can be expressed as \( \langle 1, P1, P2, 3, 4, 5, P3, P4, P5, 12, 12\rangle \). We call PDD is a complete PDD if all adjacent nodes \( <N_i, N_j> \) in PDD satisfy \( <N_i, N_j> \in PDD \land (N_i, N_j) \in E \), otherwise the PDD is a part PDD.

IV. DOMAIN REDUCTION CONSIDERING DATA DEPENDENCE

DRD begins with the analysis of the program. It generates CFG, and initializes the state of PDD as \( <N_i, N_j> \).
First, use the mutation operator on target node \( N_p \) to generate a set of mutations. Then combine the necessity condition \( C_n \) collection marked by \( C \), and build the constraint system for each element of the necessity condition collection \( C \), and automatically detect equivalent mutants, and solve the constraint system to generate the test data at last. PDD generation is the key to build constraint system. The data process flow graph of DRD is shown in figure 2, and its sequence operator may refer to Z language [27]. Process can be divided into four phases: (1) pretreatment; (2) constrain system building; (3) detecting equivalent mutants; (4) constraint system solving.

![Figure 2. Dataflow diagram](image)

**A. PDD Generation**

Set \( \text{PDD}_0 = <N_s, N_g> \). PDD generation includes key PDD generation and complete PDD building. Search process calculates \( LD(p) \), set \( LD(p) = \{N_{d1}, N_{d2}, \ldots, N_{dn}\} \), generates n PDDs. Each new PDD generated with data dependence until the PDD is complete PDD, i.e. \( N_{di} \) is bigger than \( N_p \); (2) if \( N_i \) is a branching node, \( N_j \) is less than all children nodes’ sequence number of \( N_i \). In addition, when new PDD generated, if the insertion node is non-branching node, modify the set of node that has data dependent on the insertion node after it. Formal description is as follows: for new insertion node \( N_k \), if \( D(N_k) \neq \emptyset \), then for arbitrary node \( N_i, N_j \in \text{PDD} \land i > k \), modify the set of data dependence of node \( N_k \) to \( U(N_k) \cup D(N_k) \) when \( U(N_i) \cap D(N_k) = \emptyset \). If it is a branching node and conflict with other node, remove all the other nodes under control of the branch node. The modify process after insert node we called modify process of influence with data dependence.

![Figure 3. A search tree for PDD generation](image)

As the program is shown in figure 1, given the starting node \( l \) and goal node \( 14 \), there is \( \text{PDD}_0 = <1, 14> \). generation process in the first stage is shown in table I, \( PN \) is the problem node generated by the searching process.

Let \( \text{PDD} = \text{PDD}_{\text{1st}} \), first stage generate an incomplete execution path of program, and it cannot build the constraint system, we need to complete it by PDD generation in the second stage. Get any two adjacent nodes \( N_i, N_j \) in PDD, if \( (N_i, N_j) \not\in E \), searching process generate arbitrary path that satisfies the condition, inserting the nodes in the path into PDD according to insert rules, and execute modify process of influence with data dependence until the PDD is complete PDD, i.e. \( \text{PDD} = <1, P_1, P_2, 3, 4, 5, \ldots, \{3\}, \ldots, \{5\}> \), \( P_1, P_2, 3, 4, 5 \) are node set which is generated by PDD generation, and \( (P_1, P_2) \) are node set which is generated by PDD generation.
to 4 by searching process, and select a path not
conflicting with existed nodes in PDD to insert into
the PDD, we insert node 3 into PDD here and execute the
modification process of influence with data dependence,
and get arbitrary path \(<4, 5, P3, P4, P5>, <4, 5, P3, 6, 7,
8, P4, P5>, \cdots\) through the adjacent nodes \((4, P5)\),
we insert node 5, P3, P4 into PDD and execute modify
process of influence with data dependence to get the complete PDD

\[ PDD = \langle 1, P1, P2, 3, 4, 5\rangle, P3:4, P4:5, P5:4, 5, P6:4, P7:4, 5\rangle, 14 > \]

TABLE I. DEMONSTRATION OF PDD GENERATION IN THE FIRST STAGE

<table>
<thead>
<tr>
<th>layer</th>
<th>PDD</th>
<th>PN</th>
<th>LD</th>
<th>New PDD</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>PDD0=&lt;1,14&gt;</td>
<td>P7</td>
<td>{4,5,7,8,10,11,c}</td>
<td>PDD1,PDD2 ,PDD3,PDD4,PDD5,PDD6,PDD7</td>
</tr>
<tr>
<td>1</td>
<td>PDD1=&lt;1,4,P7:4&gt;, 14&gt;</td>
<td>P2</td>
<td>{c}</td>
<td>PDD11</td>
</tr>
<tr>
<td>2</td>
<td>PDD11=&lt;1,P2,4, P7:4&gt;,14&gt;</td>
<td>P1</td>
<td>{c}</td>
<td>PDD111</td>
</tr>
<tr>
<td>3</td>
<td>PDD111=&lt;1,P1,P2, P4,P7:4&gt;,14&gt;</td>
<td>P6</td>
<td>{4,5,7,10, c}</td>
<td>PDD1111, PDD1112, PDD1113</td>
</tr>
<tr>
<td>4</td>
<td>PDD1111=&lt;1,P1,P2, 4,P6,P7:4&gt;,14&gt;</td>
<td>P5</td>
<td>{4,5,7,8,10,11,c}</td>
<td>PDD11111, PDD11112, PDD11113</td>
</tr>
<tr>
<td>5</td>
<td>PDD11111=&lt;1,P1,P2, 4,P5,P6,P7:4&gt;,14&gt;</td>
<td>{}</td>
<td>{}</td>
<td>{}</td>
</tr>
</tbody>
</table>

B. Search Process

Search process includes searching problem nodes and
generating arbitrary path between nodes. Searching
problem node is searching start node of critical branch,
insert critical branch into PDD earlier in order to reduce
the generation number of infeasible program path and
improve the efficiency of program execution.

Search process measures all branching nodes before specify
node, if there is only one path from branch node which
can reach specify node, the branch is critical branch and
return branching node as problem node. As searching the
critical branch of specify node, descend waiting branching
nodes in CFG and search the closest problem node at first, i.e. in PDD=<3, P6, 14, 15>, all \((P3, P6), (P6, P7)\) and \((P7, 14)\) are critical paths
for node 14, and return the node P7.

C. Constraint System Building

PDD is the program execution node sequence, and N: LDP(N) contains the number node and the last
definition node, i.e. formula (1), there are 12 nodes including mutation node, and 12 sets of data dependence.
We cut CFG by PDD, remove the node not in PDD and add the back edge with data dependence, Demonstration
of C graph of CFG split by formula (1) is shown in figure 4.

The PDD is the path with data dependence from start
node \(N_i\) to goal node \(N_g\). \(C_n\) is necessity condition, \(P\) is a
sequence of paths built by reachability condition, initialize to \(\leftarrow\), \(N\) points to the node of PDD, \(C\) is
predicate expression of reachability condition generated
by \(P\), initialize to "". The algorithm can be divided into
two parts: (1) clear data dependence line in cutting CFG;
(2) clear control line, which generates constraint
expression \(C\) by \(P\), build predicate expression of
constraint system by combine \(C\) and necessity condition.

Building constraint system by formula (1), after step 1
is as follow: there are PDD = <14>, \(P = <1, P1, P2, 3, 4,
5\>, P3, P4, P5, P6, P7, 14>, change 5’ to \(b = a\), branch
predicates are BP(P3, P4) = "b <= c", BP(P4, P5) = "a <=
c", BP(P5, P6) = "b + a > c", BP(P6, P7) = "b != c", BP(P7,
14) = "b = a \lor a = c". Use mutation operator SCR on
node 14, there is 14: \(\Delta type = type\), necessity condition is
\(C_n = ((\text{type} = \text{"ISOSCELES"}) \lor \text{\((\text{type} = \text{"SCALENE"})\)))\) =
true. In step 2, execute the branch predicates of the path \(P\),
return value as follows:

\[ (a >= 1 \land b >= 1 \land c >= 1) \land (a > b) \land (b <= c) \land (a
\leq c) \land (b + a > c) \land (b != c) \land (b = a \lor a = c) \land (true) \].
Then split Disjunction expression by permutation and combination, and get conjunction expression as following:

\[ (a \geq 1 \land b \geq 1 \land c \geq 1) \land (a > b) \land (b <= c) \land (a <= c) \land (b + a > c) \land (b != c) \land (b = a) \land (true) \].

\[ (a \geq 1 \land b \geq 1 \land c \geq 1) \land (a > b) \land (b <= c) \land (a <= c) \land (b + a > c) \land (b != c) \land (a = c) \land (true) \].

D. Auto-detection of Equivalent Mutants

If the mutant is equivalent mutant, it will always get the same output as the original program, so the test case cannot kill it. If we can automatically detect the equivalent mutants, we can save much TDG time and improve the TDG efficiency. Strategies for Detecting Equivalent Mutants are as follows:

1. Negation [26]

   1) Negation. Constraint C1 is the negation of C2 iff they describe non-overlapping domains and cover the entire domain.

2) Partial Negation. Constraint C1 is a partial negation of C2 if they describe non-overlapping domains and do not cover the entire domain.

3) Semantically Equal. Two constraints C1 and C2 are semantically equal if they describe the same domain.

4) Syntactically Equal. Two constraints C1 and C2 are syntactically equal if they describe the same domain and same string of symbols.

2. Constraint Splitting

Give two constrains \((x + y) > 0\) and \((x < 0)\). The negation strategy cannot get the two constraints conflict, constraint splitting is used to detect this conflict. Give two constraints C1 and C2. Then give two new constraints C3 and C4 that C1 \(\Rightarrow\) C3 \(\lor\) C4. If both C3 and C4 conflict with C2, we can get C1 conflicts with C2.

3. Constants Comparison [26]

Let A be the constraint \((X \text{rop1} K_1)\) and B be the constraint \((X \text{rop2} K_2)\) where X is a variable, rop1 and rop2 are relational operators, and K1 and K2 are constants, we can often decide whether A conflicts with B by evaluating the two constants and relational operators. If we use the negation strategy to constraints \((x > 1)\) and \((x < 0)\), it can partially negate or negate to \((x < 1)\) or \((x < 1)\), but neither \((x > 0)\) nor \((x < 1)\) is syntactically equal to \((x < 0)\), so we cannot get they conflict. For this problem, constants comparison can be used to get the two constraints conflict.

There is \(p' = (a \geq b) \land \text{rop2}(a,b,c) \land (a \leq c) \land (b \geq c) \land (b = a) \land (true)\).

Initialize the DDS for a, b and c in formula \((1)''\) \(p'' = (a \geq b) \land \text{rop2}(a,b,c) \land (a \leq c) \land (b \geq c) \land (b = a) \land (true)\).

\[ (a \geq 1 \land b \geq 1 \land c > 1) \land (a > b) \land (b <= c) \land (a <= c) \land (b + a > c) \land (b != c) \land (a = c) \land (true) \].

\[ (a \geq 1 \land b \geq 1 \land c > 1) \land (a > b) \land (b <= c) \land (a <= c) \land (b + a > c) \land (b != c) \land (a = c) \land (true) \].

E. Constraint System Solving

Constraint system solving process is a process of operate domain reduction indefinite form. First, initial the program input. Meanwhile it saves variable and its initial domain into DDS.

<table>
<thead>
<tr>
<th>Step</th>
<th>GetSplit Condition</th>
<th>SplitPoint</th>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Start</td>
<td>-</td>
<td>-</td>
<td>-100</td>
<td>-100</td>
<td>-100</td>
</tr>
<tr>
<td>2.a:=1</td>
<td>rexpr is a constraint</td>
<td>-</td>
<td>1..100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>3.b:=1</td>
<td>rexpr is a constraint</td>
<td>-</td>
<td>1..100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>4.c:=1</td>
<td>rexpr is a constraint</td>
<td>-</td>
<td>1..100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>5.a&gt;b</td>
<td>(domain.Bot&lt;=rdomain.Bot) and (domain.Top&lt;=rdomain.Top)</td>
<td>(100-1)/2+1</td>
<td>51..100</td>
<td>1.50</td>
<td>1..100</td>
</tr>
<tr>
<td>6.b&lt;=c</td>
<td>(domain.Bot&lt;=rdomain.Bot) and (domain.Top&lt;=rdomain.Top)</td>
<td>(50-1)/2+1</td>
<td>51..100</td>
<td>1.25</td>
<td>100..100</td>
</tr>
<tr>
<td>7.a&lt;c</td>
<td>(domain.Bot&lt;=rdomain.Bot) and (domain.Top&lt;=rdomain.Top)</td>
<td>(100-51)/2+1</td>
<td>51..100</td>
<td>1.25</td>
<td>51..100</td>
</tr>
<tr>
<td>8.b+a&gt;c</td>
<td>(domain.Bot&lt;=rdomain.Bot) and (domain.Top&lt;=rdomain.Top)</td>
<td>(100-75)/2+75</td>
<td>69..75</td>
<td>19..75</td>
<td>51..100</td>
</tr>
<tr>
<td>9.b!=c</td>
<td>-</td>
<td>-</td>
<td>69..75</td>
<td>19..75</td>
<td>51..100</td>
</tr>
<tr>
<td>10.a=c</td>
<td>-</td>
<td>-</td>
<td>75</td>
<td>19..75</td>
<td>75</td>
</tr>
</tbody>
</table>

TABLE II. PROCESS OF SOLVING THE CONSTRAINT SYSTEM FOR FORMULA (1)''
V. EXPERIMENTAL ANALYSIS

Experimental environment: CPU is Inter E7400, CPU frequency is 2.80GHz, memory size is 4G, hard disk size is 160G and OS is Ubuntu 10. CBT is assembled in tool Godzilla [3], CAT uses tool TESTGEN [1] and DRD is a small TDG tool implemented by Java. The experimental program is shown in table III. All the programs we used to experiment are simple structures, and these programs have distinct characteristics.

<table>
<thead>
<tr>
<th>Program</th>
<th>Description</th>
<th>Statements</th>
<th>Mutants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mid [15]</td>
<td>Return the middle value of three given integers</td>
<td>11</td>
<td>26</td>
</tr>
<tr>
<td>TriType</td>
<td>Classify the triangle as equilateral, isosceles, scalene or invalid</td>
<td>22</td>
<td>44</td>
</tr>
<tr>
<td>MinMax</td>
<td>Return the maximum and minimum elements from an integer array</td>
<td>10</td>
<td>23</td>
</tr>
<tr>
<td>GCD</td>
<td>Return the greatest common divisor of two given positive integers</td>
<td>9</td>
<td>19</td>
</tr>
<tr>
<td>Sample [18]</td>
<td>A sample function used in paper [18]</td>
<td>17</td>
<td>30</td>
</tr>
</tbody>
</table>

We use the CBT, CAT and DRD with detecting equivalent mutants to generate test data and the assess value for experimental are as follow:

1. Success ratio of test data generation, which is the same to mutation score. We set the run time threshold to 100s. If the valid test data is generated in run time threshold, we successfully generate the test data. We use MS to record the success ratio as assess its reliability.

2. Average time of successfully generate the test data marked as ASuc and maximum time of successfully generate the test data marked as MSuc to assess execution efficiency.

![Figure 5. Comparison diagram of mutation score](image5)

![Figure 6. Comparison diagram of total run time](image6)

We use CBT combined with DDR, CAT and DRD with detecting equivalent mutants to those programs to generate the test data. The result of MS is shown in figure 5. DRD is higher than CBT in MS, but lower than CAT except for TriType. CAT is Goal-oriented TDG method, so CAT always has a high MS.

![Figure 7. Comparison diagram of ASuc](image7)

![Figure 8. Comparison diagram of MSuc](image8)

Although DRD has less MS than CAT, but DRD reduce 3%-8% runtime than CAT as shown in figure 6. If there are more branch statements, DRD will take less run time than CBT. So we can get the conclusion that DRD has higher MS and reduces the total run time.

The results of ASuc and MSuc are shown in figure 7 and 8. CBT has the fastest TDG and lower run efficiency. Although CAT has a highest MS, while CAT has highest ASuc and MSuc. DRD combined the advantage of CBT and CAT, DRD has lower ASuc and MSuc than CAT, and it also get higher MS than CBT.

MS is conflict with run time. High MS always spend more run time. Experiment results show that DRD has better execution efficiency than CBT and CAT. It can successfully judge the equivalent mutants and decrease the possibility to select the infeasible path. It also can solved influences on constraint systems caused by the multiple conditional branch statement.

VI. CONCLUSION

Mutation testing has been developed for 30 years but remains active. It is not only applied in unit tests but also contributes to a lot of theoretical research in interface testing, aspect-oriented testing, object-oriented testing and contract testing. Mutation testing is a very labor-intensive process, which spends most resource in TDG. Automatically TDG process can greatly improve the efficiency of software testing; thereby reduce the cost of software development. On the one hand, Mutation testing is a testing strategy to evaluate the completeness of test cases, which helps the testers to control the quality of tests and builds confidence for software accuracy. On the
other hand, mutation testing can automatically generate complete test cases, which greatly improved the quality and efficiency of software testing. This paper proposed a new method DRD combined with goal-oriented method for TDG with data dependence. It added the detecting of equivalent mutants and solved the problem of branch statement composed by many conditions. It builds constraint system by control flow analysis, data flow analysis, symbols execution and mutation information, used domain reduction technology and solved the constraint system by selecting random minimum variables in selected domains and verified with back substitution. It adds the detecting of equivalent mutants and solves the effect on the constraint systems caused by branch statement, which is composed by multiple conditions. Experimental results showed that this method improved the success rate and execution efficiency of test data generation to a large extent though further improvement in total run time is needed. In this paper, data dependence has been considered in PDD generation process; it insert the problem nodes and those has data dependence on them into the search tree firstly, but in the experiment of program TriType, it is always faster to find solutions in constraint system building without data dependence. The next step is to consider how to evaluate the insertion of data dependence according to the program.

REFERENCES


