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Abstract

Random testing (RT) is a fundamental software testing technique. *Adaptive random testing* (ART), an enhancement of RT, generally uses fewer test cases than RT to detect the first failure. ART generates test cases in a random manner, together with additional test case selection criteria to enforce that the executed test cases are evenly spread over the input domain. Some studies have been conducted to measure how evenly an ART algorithm can spread its test cases with respect to some distribution metrics. These studies observed that there exists a correlation between the failure detection capability and the evenness of test case distribution. Inspired by this observation, we aim to study whether failure detection capability of ART can be

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enhanced by using distribution metrics as criteria for the test case selection process. Our simulations and empirical results show that the newly proposed algorithms not only improve the evenness of test case distribution, but also enhance the failure detection capability of ART.

Keywords: Software Testing, Random Testing, Adaptive Random Testing, Test Case Distribution, Discrepancy, Dispersion.

1 Introduction

Improving software quality has become one of the important objectives for the current software industry (NIST, 2002). Software testing, a major approach to software quality assurance (Hailpern and Santhanam, 2002), is widely acknowledged as a vital activity throughout the software development process. Many software testing methods are accomplished by defining test objectives, selecting some inputs of the program under test as *test cases*, executing the program with these test cases, and analysing testing results (Beizer, 1990). Since software normally has an extremely large *input domain* (that is, the set of all possible program inputs), testers are always required to select a portion of the input domain as test cases such that software failures can be effectively detected with this selected portion of test cases. A large number of software testing methods have been proposed to guide the test case selection.

Random testing (RT), a basic test case selection method, simply selects test cases in a random manner from the whole input domain (Hamlet, 2002; Myers, 2004). RT has been popularly applied to assess the software reliability (Girard and Rault, 1973; Thayer et al., 1978). In addition, RT has been used in different areas to detect software failures. For example, Miller et al.

(1990, 1995) have used RT to test UNIX utility programs, and reported that a large number of UNIX programs have been crashed or hanged by RT. Forrester and Miller (2000) applied RT to test Windows NT applications, and it was observed that 21% of applications were crashed and an additional 24% of applications were hanged. RT has also been used in the testing of communications protocol implementations (West and Tosi, 1995), graphical user interfaces (Dabóczi et al., 2003), Java Just-In-Time compilers (Yoshikawa et al., 2003), embedded software systems (Regehr, 2005), and image processing applications (Mayer and Guderlie, 2006). Moreover, the RT technique has been implemented in many industrial automatic testing tools, such as those developed by IBM (Bird and Munoz, 1983), Microsoft (Slutz, 1998), and Bell Labs (Godefroid et al., 2005).

However, some people (Myers, 2004) criticised that RT may be the "least effective" testing method for using little or no information about the program under test to guide its test case selection. One common characteristic of faulty programs is that the *failure-causing inputs* (program inputs that can reveal failures) are usually clustered together, as reported by White and Cohen (1980), Ammann and Knight (1988), Finelli (1991), and Bishop (1993). Chen et al. (2004) investigated how to improve the failure detection capability of RT under such a situation. Given that failure-causing inputs tend to cluster into contiguous regions (namely *failure regions* (Ammann and Knight, 1988)), non-failure regions are also contiguous. Therefore, if a test case does not reveal any failure, it is very likely that its neighbours would not reveal a failure either. In other words, given the same number of test cases, a more even spread of test cases should have a better chance to detect a failure. When RT is used to detect software failures, inputs are usually selected as test cases according to uniform distribution, that is, all inputs have the same probability of being selected as test cases. Therefore, an input that is adjacent to some previously executed but non-failure-causing test cases may still be selected as the next test case. However, such a test case is also unlikely to reveal failure. Aiming at enhancing the failure detection capability of RT, Chen et al. (2004) proposed a new approach, namely *adaptive random testing* (ART). Like RT, ART also randomly generates test cases from the input domain. But ART uses additional criteria to guide the test case selection in order to ensure that all test cases are evenly spread over the whole input domain. Different *test case selection criteria* give rise to different ART algorithms, such as *fixed-sized-candidate-set ART* (FSCS-ART) (Chen et al., 2004), *lattice-based ART* (Mayer, 2005), and *restricted random testing* (Chan et al., 2006). Previous simulations and empirical studies conducted on these algorithms have shown that in general, when failure-causing inputs are clustered into contiguous failure regions, ART uses fewer test cases to detect the first failure than pure RT.

Chen et al. (2007b) have used several metrics to measure and compare the test case distributions of various ART algorithms. Among these metrics, *discrepancy* and *dispersion* are two metrics commonly used to measure the equidistribution of sample points. Chen et al. (2007b) investigated both the test case distributions and the failure detection capabilities of some ART algorithms, and they empirically justified that there exists a correlation between the test case distribution and the failure detection capability of an ART algorithm. For example, the test case selection criterion in FSCS-ART may bring a large value of discrepancy when the dimension of input domain is high; while the failure detection capability of FSCS-ART becomes worse as the dimension of input domain increases.

Previous studies (Chen et al., 2007b) have shown that an even spread of test cases is correlated to a high failure detection capability. Since discrepancy and dispersion reflect different aspects of the test case distribution, we are motivated to apply these metrics as criteria in the test case selection process of ART, aiming at improving the evenness of test case distribution and the failure detection capability of ART. However, adopting distribution metrics as the new test case selection criteria of ART is not so straightforward as it looks. As will be shown in our study, if an ART algorithm applies discrepancy or dispersion as the standalone test case selection criterion, it will have an uneven distribution of test cases as well as a poor failure detection capability. In this paper, we also investigate whether the performance of ART can be enhanced if discrepancy and dispersion are integrated with existing test case selection criteria. Our study delivers some interesting results.

Our work is conducted on a particular ART algorithm, namely FSCS-ART. The structure of the paper is as follows. In Section 2, we give some preliminary background of ART and present the basic concepts of discrepancy and dispersion. We propose two new test case selection criteria based on discrepancy and dispersion in Section 3. In Section 4, we investigate the performance of ART algorithms that solely use discrepancy or dispersion to select test cases. In Section 5, we propose some new ART algorithms where discrepancy and dispersion are integrated with other criteria in the test case selection process. The simulations and experimental results of these new algorithms will also be reported in this section. Finally, Section 6 presents the discussion and conclusion.

2 Background

2.1 Notation

For ease of discussion, we introduce the following notation, which will be used in the rest of this paper.

- E denotes the set of already executed test cases.
- I denotes the input domain.
- d_I denotes the dimension of I, which is the number of input parameters of the program under test.
- ND denotes N-dimension, where $N = 1, 2, \cdots, d_I$.
- $|\cdot|$ denotes the size of a set. For example, $|E|$ and $|I|$ denote the size of E and I, respectively.
- $dist(p, q)$ denotes the Euclidean distance between two points p and q.
- $\eta(p, E)$ denotes p's nearest neighbour in E.

2.2 One test case selection criterion of adaptive random testing

Generally speaking, besides randomly generating program inputs, ART uses additional criteria to select inputs as test cases in order to ensure an even spread of test cases. *Fixed-sized-candidate-set ART* (FSCS-ART) (Chen et al., 2004) is one typical ART algorithm. In FSCS-ART, there exist two sets of test cases, the *executed set* denoted by E and the *candidate set* denoted by C. E contains all test cases which were already executed but did not reveal any failure; while C contains k randomly generated inputs, where k is fixed throughout the testing process. The test case selection criterion of FSCS-ART is as follows. For any $c_j \in C$, we define

$$d^j_{distance} = dist(c_j, \eta(c_j, E)). \tag{1}$$

We choose a candidate c_b as the next test case, if its $d^b_{distance}$ is the largest amongst all candidates, that is, $\forall j = 1, 2, \cdots, k, d^b_{distance} \geq d^j_{distance}$. The test case selection criterion of FSCS-ART is referred to as $S_{distance}$ in this paper.

Figure 1 gives the detailed algorithm of FSCS-ART. Chen et al. (2004) have observed that the effectiveness of FSCS-ART can be significantly improved by increasing k when $k \leq 10$. However, the effectiveness appears to be independent of the value of k when $k > 10$. In other words, $k = 10$ is close to the optimal setting of FSCS-ART. Hence, they have used $k = 10$ in their investigation. In this paper, we also set the default value of k as 10.

1. Input an integer k, where $k > 1$.
2. Set $n = 0$ and $E = \{\}$.
3. Randomly generate a test case t from I, according to uniform distribution.
4. Run the program with t as the test case.
5. **while** (no failure has been revealed)
6.   Add t into E, and increment n by 1.
7.   Randomly generate k program inputs (candidates) from I, according to uniform distribution, to form a candidate set $C = \{c_1, c_2, \cdots, c_k\}$.
8.   Find $c_b \in C$ according to $S_{distance}$.
9.   Set $t = c_b$.
10.   Run the program with t as the test case.
11. **end_while**
12. Report the detected failure.
13. Exit.

Figure 1: The algorithm of FSCS-ART

In this paper, for convenience of discussion and illustration, we assumed that the program under test only has numeric inputs. Applications of ART on non-numeric programs can be found in the studies of Merkel (2004), Kuo (2006) and Ciupa et al. (2006, 2008).

2.3 Failure detection capability of adaptive random testing

F-measure, one commonly-used metric for measuring the effectiveness of a testing method, is defined as the expected number of test cases required to detect the first failure. As explained by Chen and Merkel (2008), F-measure is more preferable than other metrics to evaluate and compare the effectiveness of ART/RT. Hence, we will also use F-measure as the effectiveness metric in this study.

The F-measure of ART (denoted by F_{ART}) depends on many factors, so it is very difficult to theoretically derive the value of F_{ART}. Chen et al. (2007c) have extensively studied F_{ART} for FSCS-ART via a series of simulations. In each simulation, the failure rate θ (the ratio of the number of failure-causing inputs to the number of all possible inputs) and the failure pattern (the shapes of failure regions together with their distribution over the input domain I) were predefined. Test cases were selected one by one until a point inside the failure region was picked by ART (that is, a failure was detected). The number of test cases required to detect the first failure in each test trial, referred to as F-count (Chen and Merkel, 2008), was thus obtained. Such a process was repeated for a sufficient number of times until the mean value of F-counts could be regarded as a reliable approximation for F_{ART} within 95% confidence level and $\pm 5\%$ accuracy range (details on how to get the reliable approximation can be found in the study of Chen et al. (2004)).

Chen et al. (2007c) have conducted an experiment to evaluate the failure detection capability of ART when failure-causing inputs cluster together. The details of this experiment are given as follows. I was set to be a hypercube and d_I was set as either 1, 2, 3 or 4. A single hypercube failure region was randomly placed inside I. The size of the failure region was decided by the failure rate θ, where θ = 0.75, 0.5, 0.25, 0.1, 0.075, 0.05, 0.025, 0.01, 0.0075, 0.005, 0.0025, 0.001, 0.00075, 0.0005, 0.00025, 0.0001, 0.000075, or 0.00005.

ART was originally proposed to enhance the failure detection capability of RT, whose F-measure (denoted by F_{RT}) is theoretically equal to $1/\theta$ when test cases are selected with replacement and according to uniform distribution. In this paper, we will use the *ART F-ratio* ($= F_{ART}/F_{RT}$) to measure the enhancement of ART over RT. If F-ratio is smaller than 1, it means that ART outperforms RT.

2.4 Discrepancy and dispersion as test case distribution metrics

Discrepancy and dispersion are two commonly used metrics for measuring the equidistribution of sample points. Intuitively speaking, low discrepancy and low dispersion indicate that sample points are reasonably equidistributed.

Points sequences with low discrepancy and low dispersion are very useful in various areas, such as numerical integration (Hua and Wang, 1981), global optimisation (Niederreiter, 1986), and path planning (Branicky et al., 2001). Recently, Chen and Merkel (2007) have proposed to apply low-discrepancy and low-dispersion sequences to generate test cases, aiming at improving the effectiveness of RT. However, their approach is different from what is proposed in this study.

Chen et al. (2007b) have used discrepancy and dispersion to measure the evenness of the test case distribution of FSCS-ART (as well as some other ART algorithms). For ease of discussion, the detailed definitions of these metrics are given as follows.

- **Discrepancy** (denoted by $M_{Discrepancy}$). Given $\mathcal{N}$ sample points inside I, discrepancy indicates whether different regions in I have an equal density of points. One standard definition of discrepancy (Niederreiter, 1992) is as follows.

$$discrepancy = \sup_{\mathcal{D}} \left| \frac{\mathcal{A}(\mathcal{D})}{\mathcal{N}} - \frac{|\mathcal{D}|}{|I|} \right|, \tag{2}$$

  where sup refers to the supremum of a data set, $\mathcal{D}$ is any subdomain of I, and $\mathcal{A}(\mathcal{D})$ is the number of points inside $\mathcal{D}$. Due to the infinite number of $\mathcal{D}$, it is very difficult, if not impossible, to derive the value of discrepancy exactly according to Equation 2. Therefore, Chen et al. (2007b) used the following definition to approximate the discrepancy.

$$M_{Discrepancy} = \max_{i=1}^{m} \left| \frac{|E_i|}{|E|} - \frac{|\mathcal{D}_i|}{|I|} \right|, \tag{3}$$

  where $\mathcal{D}_1, \mathcal{D}_2, \cdots, \mathcal{D}_m$ denote m rectangular subdomains of I, whose locations and sizes are randomly defined; and $E_1, E_2, \cdots, E_m$, which are subsets of E, denote the sets of test cases that are located inside $\mathcal{D}_1, \mathcal{D}_2, \cdots, \mathcal{D}_m$, respectively.

  In Equation 3, m cannot be too small; otherwise, Equation 3 may not deliver a reliable approximation of Equation 2. m cannot be too large either, because the computational overhead of Equation 3 increases with the increase of m. To balance the computation and accuracy, m has been set as 1000 by Chen et al. (2007b). In this paper, m is also set as 1000 to be consistent with the previous work.

- **Dispersion** (denoted by $M_{Dispersion}$). Given a set of points inside I, dispersion intuitively indicates whether there is a large empty spherical region (containing no point) in I. The size of this empty region is usually reflected by the maximum distance that any point has from its nearest neighbour (Niederreiter, 1992), as shown in Equation 4.

$$M_{Dispersion} = \max_{i=1}^{|E|} dist(e_i, \eta(e_i, E \setminus \{e_i\})), \tag{4}$$

where $e_i \in E$.

Chen et al. (2007b) conducted some simulations to measure the values of discrepancy and dispersion of some ART algorithms. In these simulations, d_I was set as 1, 2, 3 and 4, $|E|$ was set as from 100 to 10000. A sufficient amount of data were collected in order to get a reliable mean value of a certain metric within 95% confidence level and ±5% accuracy range (details on how to get a reliable mean value can be found in the study of Chen et al. (2007b)).

Chen et al. (2007b) observed that FSCS-ART generally has a small value of $M_{Dispersion}$, and that FSCS-ART normally yields different densities of test cases for different subdomains inside I, which, in turn, results in a large value of $M_{Discrepancy}$.

3 Discrepancy and dispersion as test case selection criteria

As observed in previous studies (Chen et al., 2007b), the performance of an ART algorithm has a correlation with the test case distribution. This has motivated us to consider whether the performance of ART can be enhanced if we enforce a smaller discrepancy or a smaller dispersion during its test case selection process. Obviously, such an enforcement can be achieved by using discrepancy or dispersion as the test case selection criterion in an ART algorithm. The following outlines how discrepancy and dispersion could be used as test case selection criteria in FSCS-ART.

- **Test case selection criterion based on discrepancy (denoted by $\mathbf{S_{discrepancy}}$).**

  Given a candidate set $C = \{c_1, c_2, \cdots, c_k\}$ in FSCS-ART, for any $c_j \in C$, we define

  $$d^j_{discrepancy} = \max_{i=1}^{m} \left| \frac{|E'_i|}{|E'|} - \frac{|\mathcal{D}_i|}{|I|} \right|, \tag{5}$$

  where $E' = E \cup \{c_j\}$, and $\mathcal{D}_1, \mathcal{D}_2, \cdots, \mathcal{D}_m$ denote m randomly defined subdomains of I, with their corresponding sets of test cases being denoted by $E'_1, E'_2, \cdots, E'_m$, which are subsets of E'. We select a candidate c_b as the next test case, if such a selection will give rise to the smallest discrepancy than other selections, that is, $\forall j = 1, 2, \cdots, k, d^b_{discrepancy} \leq d^j_{discrepancy}$. To be consistent with the previous study (Chen et al., 2007b), the value of m in Equation 5 is also set as 1000 in this paper.

- **Test case selection criterion based on dispersion (denoted by $\mathbf{S_{dispersion}}$).**

  Given a candidate set $C = \{c_1, c_2, \cdots, c_k\}$ in FSCS-ART, for any $c_j \in C$, we define

  $$d^j_{dispersion} = \max_{i=1}^{|E'|} dist(e'_i, \eta(e'_i, E' \backslash \{e'_i\})), \tag{6}$$

where $E' = E \cup \{c_j\}$ and $e'_i \in E'$. We select a candidate c_b as the next test case, if such a selection will give rise to the smallest dispersion than other selections, that is, $\forall j = 1, 2, \cdots, k, d^b_{dispersion} \leq d^j_{dispersion}$.

Currently, there are totally three test case selection criteria, $S_{distance}$, $S_{discrepancy}$, and $S_{dispersion}$. In Section 4, we will study the performance of ART algorithms where each of these criteria is used as the standalone test case selection criterion. As will be shown in our study, all three criteria bring certain degrees of uneven test case distribution as well as poor failure detection capabilities under some situations. In Section 5, we further investigate whether the ART performance can be improved if various selection criteria are integrated in an ART algorithm.

4 FSCS-ART using a single test case selection criterion

We replaced $S_{distance}$ in FSCS-ART algorithm (Statement 8 in Figure 1) by $S_{discrepancy}$ and $S_{dispersion}$, and got two new algorithms, namely *FSCS-ART with $S_{discrepancy}$* (abbreviated as FSCS-ART-dc) and *FSCS-ART with $S_{dispersion}$* (abbreviated as FSCS-ART-dp), respectively. In this study, we will evaluate and compare the performance of FSCS-ART-dc, FSCS-ART-dp and the original FSCS-ART algorithm (denoted by FSCS-ART-dt hereafter for clarity).

4.1 Analysis of execution time

Mayer and Schneckenburger (2006) have theoretically analysed the execution time of FSCS-ART-dt, and reported that FSCS-ART-dt requires $O(|E|^2)$

time to select $|E|$ test cases. In this section, we attempt to analyse the execution time of FSCS-ART-dc and FSCS-ART-dp.

A straightforward method to implement FSCS-ART-dc algorithm is to randomly define m subdomains ($\mathcal{D}_1, \mathcal{D}_2, \cdots, \mathcal{D}_m$ in Equation 5) for each round of test case selection, and then to calculate $d^j_{discrepancy}$ for each candidate c_j according to Equation 5. Such a method, referred to as *dynamic-subdomains method*, requires $O(|E|)$ time to select each new test case, and thus needs $O(|E|^2)$ time for selecting $|E|$ test cases. In this study, we apply a simple method to reduce the computational overhead of FSCS-ART-dc. Instead of dynamically defining the subdomains, we define m random subdomains at the beginning of the testing process, and keep using these predefined subdomains throughout the testing process. Such a *static-subdomains method* would also allocate some memory to store the number of executed test cases inside each subdomain. Since we already know how many executed test cases are located in a subdomain, the value of $d^j_{discrepancy}$ can be calculated by first identifying those subdomains that contain c_j, and then updating only their associated $|E'_i|$s, without changing any other $|E'_i|$s. Obviously, the static-subdomains method only requires a constant time to select a new test case, and thus needs $O(|E|)$ time for selecting $|E|$ test cases. We have conducted some simulations to study the failure detection capabilities of these two methods. In brief, our static-subdomains method reduces the execution time of FSCS-ART-dc to $O(|E|)$ without sacrificing the performance of FSCS-ART-dc. Details of the failure detection capabilities of FSCS-ART-dc with the static-subdomains method will be reported in the following section (Figure 3). We also observed that FSCS-ART-dc with the dynamic-subdomains method has similar failure detection behaviours.

Apparently, the naive implementation of FSCS-ART-dp has the computational overhead in $O(|E|^3)$. However, we can reduce its computational overhead by the following simple method. For each executed test case e_i, some memory is allocated to store $dist(e_i, \eta(e_i, E\backslash\{e_i\}))$. In each round of test case selection, the value of $d^j_{dispersion}$ for a candidate c_j can be calculated simply by comparing $dist(e_i, c_j)$ with $dist(e_i, \eta(e_i, E\backslash\{e_i\}))$ for all elements in E. In other words, at the expense of some additional memory, the execution time for each round of test case selection becomes $O(|E|)$; and as a result, FSCS-ART-dp will require $O(|E|^2)$ time to select $|E|$ test cases.

We experimentally evaluated the execution time of FSCS-ART-dc and FSCS-ART-dp via some simulations. All simulations were conducted on a machine with an Intel Pentium processor running at 3195 MHz and 1024 megabytes of RAM. The ART algorithms were implemented in C language and compiled with GNU Compiler Collection (Version 3.3.4) (GCC, 2004). FSCS-ART-dt, FSCS-ART-dc and FSCS-ART-dp were implemented in a 2D space. For each algorithm, we recorded the time taken to select a number of test cases, with $|E| = 500, 1000, 1500, 2000, 2500$ and 3000. The simulation results are given in Figure 2, in which, x- and y-axes denote $|E|$ and time required to generate E, respectively. It is clearly shown that FSCS-ART-dt and FSCS-ART-dp both require $O(|E|^2)$ time to select $|E|$ test cases, while the execution time of FSCS-ART-dc is in $O(|E|)$. In other words, the experimental data are consistent with the above theoretical analysis.

4.2 Analysis of failure detection capabilities

Some simulations (with settings identical to those given in Section 2.3) were conducted to study the failure detection capabilities of FSCS-ART-dc and FSCS-ART-dp. The size of candidate set k was set as 10, same as the default setting for FSCS-ART-dt. The experimental results are given in

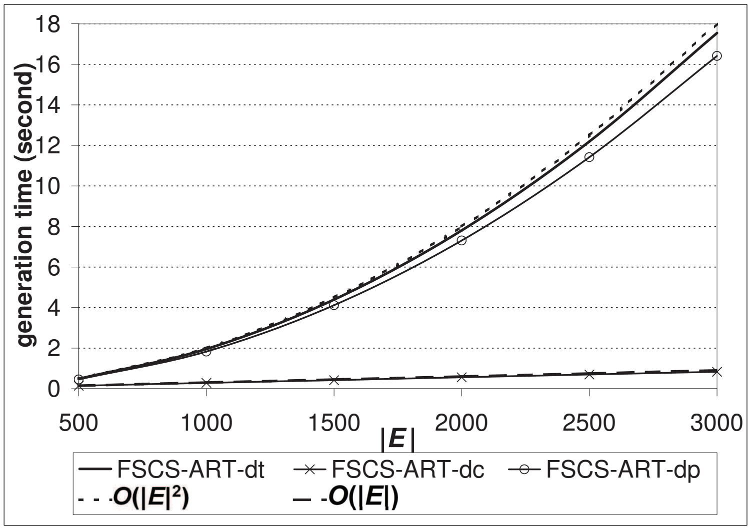
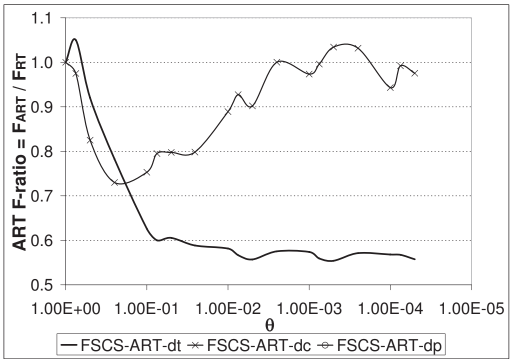


Figure 2: Comparison of execution time among FSCS-ART-dt, FSCS-ART-dc and FSCS-ART-dp

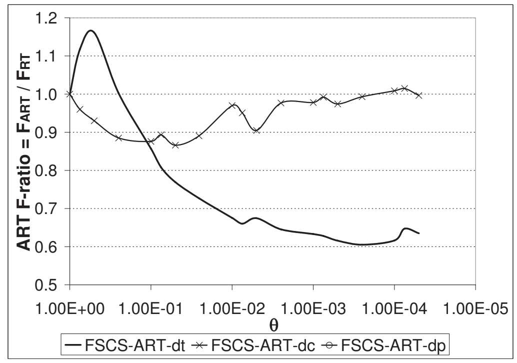
Figure 3, which also includes the previous results of FSCS-ART-dt for ease of comparison.

When simulations were conducted on FSCS-ART-dp, it was found that it is often extremely difficult, if not impossible, for FSCS-ART-dp to detect a failure, especially when d_I is low (the explanation for such a phenomenon will be given later). Therefore, this study can only collect F-measures of FSCS-ART-dp in 3D and 4D space. Figure 3 reports that FSCS-ART-dc only marginally outperforms RT, and FSCS-ART-dp usually has a higher F-measure than RT. In brief, neither discrepancy nor dispersion will result in a good failure detection capability when each of them is applied as the standalone test case selection criterion.

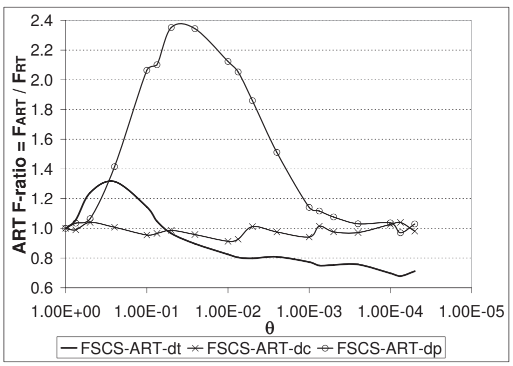
Intuitively speaking, an even spread of test cases implies a low discrepancy and a low dispersion, but neither a low discrepancy nor a low dispersion necessarily implies an even spread of test cases. Therefore, it is understandable that using discrepancy or dispersion solely in the test case selection



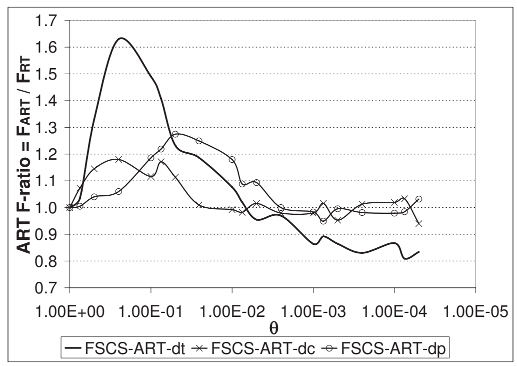
3.a FSCS-ART-dc and FSCS-ART-dp in 1D space



3.b FSCS-ART-dc and FSCS-ART-dp in 2D space



3.c FSCS-ART-dc and FSCS-ART-dp in 3D space



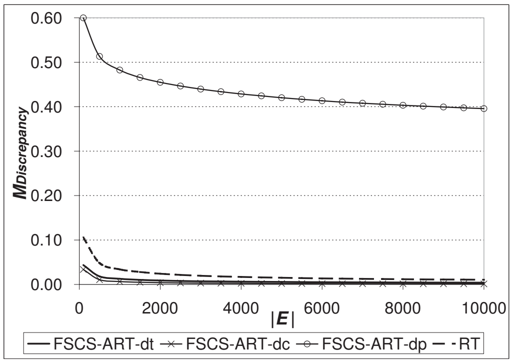
3.d FSCS-ART-dc and FSCS-ART-dp in 4D space

Figure 3: Failure detection capabilities of FSCS-ART-dc and FSCS-ART-dp

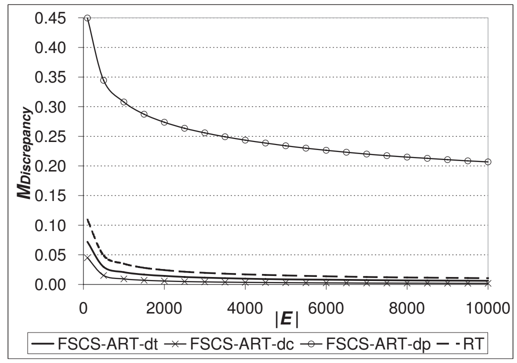
process may not deliver an even spread of test cases, and thus may not bring a good failure detection capability.

4.3 Analysis of test case distributions

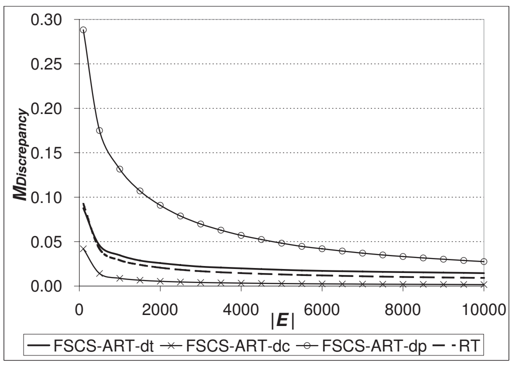
In order to further explain why these FSCS-ART-dc and FSCS-ART-dp cannot perform better than RT, more simulations were conducted to investigate their test case distributions (the experimental settings are identical to those used in Section 2.4). The simulation results are reported in Figures 4 and 5, in which, the previous results for FSCS-ART-dt and RT are also included for ease of comparison.



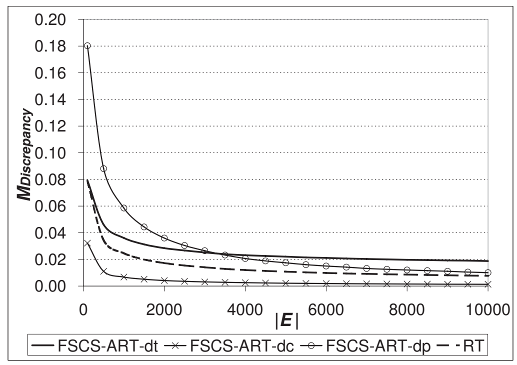
4.a $M_{Discrepancy}$ in 1D space



4.b $M_{Discrepancy}$ in 2D space



4.c $M_{Discrepancy}$ in 3D space

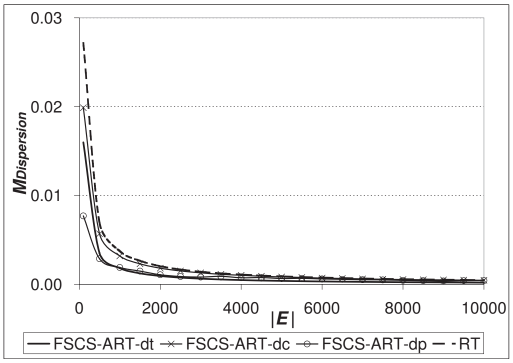


4.d $M_{Discrepancy}$ in 4D space

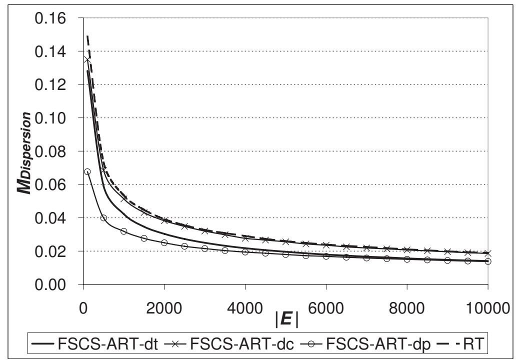
Figure 4: $M_{Discrepancy}$ of FSCS-ART-dc and FSCS-ART-dp

It is observed that FSCS-ART-dc always has a smaller $M_{Discrepancy}$ than FSCS-ART-dt and RT, as intuitively expected; however, its $M_{Dispersion}$ is larger than that of FSCS-ART-dt, and similar to that of RT. As observed by Chen et al. (2007b), a good failure detection capability of an ART algorithm is always associated with a small value of $M_{dispersion}$. FSCS-ART-dc does not have a smaller $M_{dispersion}$ than RT, although it has a small $M_{discrepancy}$. Therefore, it is understandable that FSCS-ART-dc does not significantly outperform RT. Given this observation, a small $M_{Discrepancy}$ alone is not enough to imply a good failure detection capability of ART.

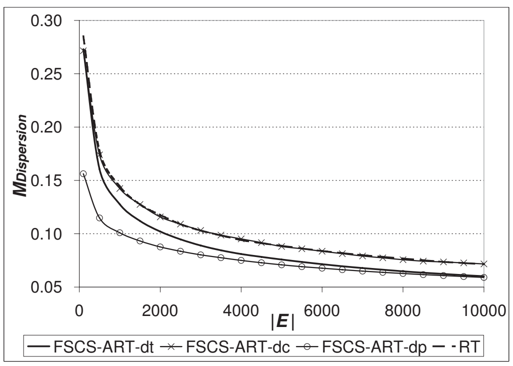
As far as FSCS-ART-dp is concerned, it can be found that FSCS-ART-dp normally has a fairly large $M_{Discrepancy}$ although its $M_{Dispersion}$ is smaller than



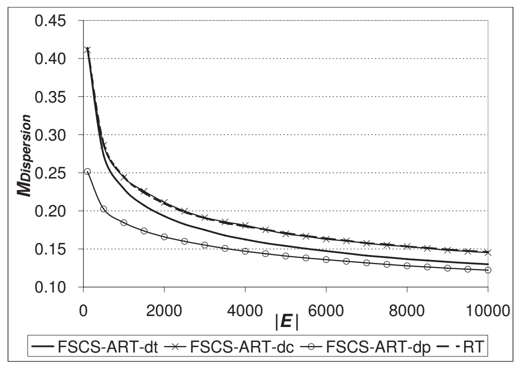
5.a $M_{Dispersion}$ in 1D space



5.b $M_{Dispersion}$ in 2D space



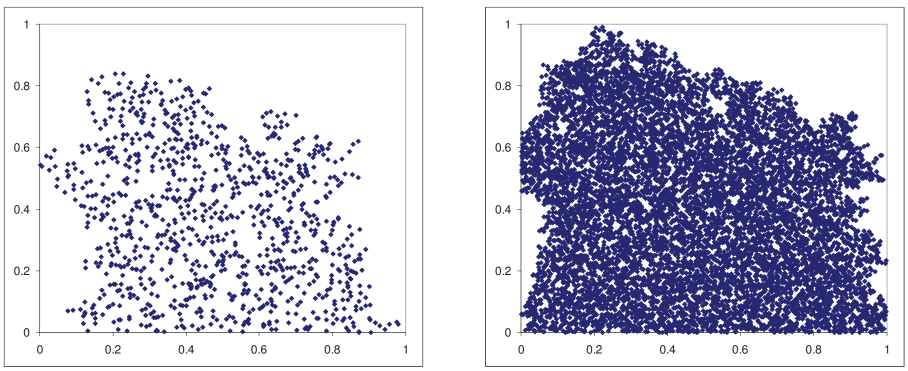
5.c $M_{Dispersion}$ in 3D space



5.d $M_{Dispersion}$ in 4D space

Figure 5: $M_{Dispersion}$ of FSCS-ART-dc and FSCS-ART-dp

that of FSCS-ART-dt. The large value of $M_{Discrepancy}$ for FSCS-ART-dp may be due to the definition of dispersion used in this study. The intuition of dispersion is to measure the largest empty spherical region inside I. Given that the sample points are uniformly distributed, the largest nearest neighbour distance (Equation 4 in Section 2.4) is a good metric to reflect the size of this empty spherical region. However, when FSCS-ART-dp solely uses such a definition to select test cases without considering the uniform distribution, it is quite likely that the selected test cases would be clustered into some regions inside I. As an example to illustrate the cluster of test cases, Figure 6 shows test cases (denoted by diamond dots) selected by FSCS-ART-dp in a 2D space, with $|E| = 1000$ and 10000, respectively. As shown in Figure 6, test cases selected by FSCS-ART-dp are not evenly spread at all. This not only explains why FSCS-ART-dp has a large $M_{Discrepancy}$, but also answers why FSCS-ART-dp has a poor failure detection capability. Briefly speaking, a fairly large $M_{Discrepancy}$ is always associated with a poor performance of an ART algorithm, no matter how small $M_{Dispersion}$ is.



6.a $|E| = 1000$ 6.b $|E| = 10000$

Figure 6: Some test cases selected by FSCS-ART-dp in 2D space

Another interesting phenomenon of FSCS-ART-dp is that its failure detection capability and $M_{Discrepancy}$ become better as d_I increases. The reason behind such a phenomenon is explained as follows. Suppose that there are two points $p = (x_1, x_2, \cdots, x_{d_I})$ and $q = (x_1+\Delta x_1, x_2+\Delta x_2, \cdots, x_{d_I}+\Delta x_{d_I})$, where x_i and $x_i+\Delta x_i$ denote the coordinates of p and q on the ith dimension ($i = 1, 2, \cdots, d_I$), respectively. Obviously, $dist(p, q) = \sqrt{\sum_{i=1}^{d_I}(\Delta x_i)^2}$. For points p and q to be very close to each other, all $|\Delta x_i|$s ought to be very small. Intuitively speaking, when d_I is higher, it is less likely that all $|\Delta x_i|$s have small values, and thus it is less likely for p and q to be physically adjacent. In other words, the uneven distribution of test cases in FSCS-ART-dp diminishes with the increase of d_I. As a result, $M_{Discrepancy}$ of FSCS-ART-dp becomes smaller with the increase of d_I, and the performance of FSCS-ART-dp improves with the increase of d_I.

5 Adaptive random testing based on distribution metrics (DM-ART)

As discussed in Section 4, although discrepancy and dispersion measure certain aspects of the evenness of test case distribution, neither of them can ensure an even spread of test cases if each of them is solely used as the test case selection criterion in ART. Compared with these two criteria, $S_{distance}$ is a better test case selection criterion, because it gives FSCS-ART-dt a small $M_{Dispersion}$, and also a good failure detection capability. However, as pointed out by Chen et al. (2007b), $S_{distance}$ is not perfect, because it may result in a relatively large $M_{Discrepancy}$ and a poor performance for some special cases. In this section, we will investigate how to improve the performance of ART by using $S_{discrepancy}$ and $S_{dispersion}$ as additional test case selection criteria to supplement $S_{distance}$.

This study proposes some new algorithms, which use $S_{discrepancy}$ and $S_{dispersion}$ to select test cases together with $S_{distance}$. Since some of test case selection criteria in the new algorithms are originally from some distribution metrics, the new algorithms are named as *ART based on distribution metrics* (DM-ART).

5.1 DM-ART algorithms with two selection criteria

The algorithms proposed in this section, which include two levels of test case selections, are called as *two-level DM-ART* (2L-DM-ART). The detailed algorithm of 2L-DM-FSCS-ART is given in Figure 7.

In 2L-DM-FSCS-ART, two test case selection criteria, denoted by S_1 and S_2, will be selected before the testing process (Statement 3 in Figure 7). One criterion will be $S_{distance}$, while the other will be either $S_{discrepancy}$ or

1. Input two integers k and l, where $k > l > 1$.
2. Set $n = 0$ and $E = \{\}$.
3. Set two selection criteria S_1 and S_2, where $(i) S_1 = S_{discrepancy}$ or $S_{dispersion}$, and $S_2 = S_{distance}$; or $(ii) S_1 = S_{distance}$, and $S_2 = S_{discrepancy}$ or $S_{dispersion}$.
4. Randomly generate a test case t from I, according to uniform distribution.
5. Run the program with t as the test case.
6. **while** (no failure has been revealed)
7.   Add t into E, and increment n by 1.
8.   Randomly generate k program inputs (candidates) from I, according to uniform distribution, to form a candidate set $C = \{c_1, c_2, \cdots, c_k\}$.
9.   Find l best candidates $c'_1, c'_2, \cdots, c'_l$ from C, according to S_1, to form a new candidate set $C' = \{c'_1, c'_2, \cdots, c'_l\}$.
10.   Find the best candidate c'_b from C', according to S_2.
11.   Set $t = c'_b$.
12.   Run the program with t as the test case.
13. **end_while**
14. Report the detected failure.
15. Exit.

Figure 7: The algorithm of 2L-DM-FSCS-ART

$S_{dispersion}$. Hence, there are totally four new ART algorithms. *2L-DM-FSCS-ART with* $S_1 = S_{discrepancy}$ *and* $S_2 = S_{distance}$ is referred to as FSCS-ART-dc-dt. The other three algorithms are similarly referred to as FSCS-ART-dp-dt, FSCS-ART-dt-dc, and FSCS-ART-dt-dp. Based on the results in Section 4.1, we can conclude that the execution time of the 2L-DM-FSCS-ART algorithms is in $O(|E|^2)$.

It should be noted that it is not expected to have a good failure detection capability when only $S_{discrepancy}$ and $S_{dispersion}$ are used together as the selection criteria. As shown in Section 4, both FSCS-ART-dc and FSCS-ART-dp exhibit certain degrees of uneven distribution of test cases. However, there does not exist any complementary relationship between discrepancy and dispersion, that is, there is no intuition why their uneven distributions will offset each other. Therefore, it is not intuitively expected that FSCS-ART-dc-dp and FSCS-ART-dp-dc outperform RT. Our simulation results on FSCS-ART-dc-dp and FSCS-ART-dp-dc are consistent with the above intuitive expectation.

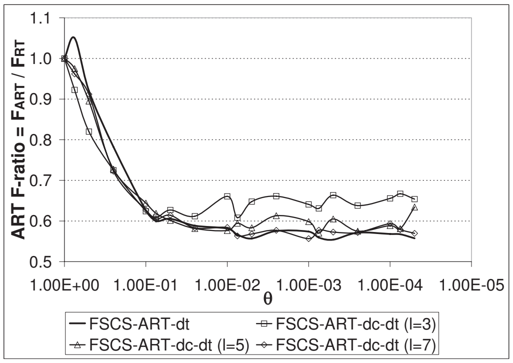
A series of simulations (with settings identical to those given in Section 2.3) were conducted to investigate the failure detection capabilities of the 2L-DM-FSCS-ART algorithms given in Figure 7. In these simulations, k is set as 10 to be consistent with previous studies of FSCS-ART-dt. l in 2L-DM-FSCS-ART algorithms cannot be either too large (that is, close to k) or too small (that is, close to 1); otherwise, one of the two selection criteria will have an effectively dominating impact on the performance of 2L-DM-FSCS-ART. In these simulations, we set $l = 3, 5$, or 7. Figures 8, 9, 10 and 11 report the simulation results on FSCS-ART-dc-dt, FSCS-ART-dp-dt, FSCS-ART-dt-dc and FSCS-ART-dt-dp, respectively. It should be noted that FSCS-ART-dp-dt with $l = 3, 5$ and FSCS-ART-dt-dp with $l = 5, 7$ in 1D space have the same problem as FSCS-ART-dp in low d_I cases, that is, an uneven distribution of test cases. Therefore, Figures 9 and 11 do not include the data for these algorithms for 1D case. The reason why these algorithms perform well for high d_I cases have been given in Section 4.

The following observations can be made from the simulation results.

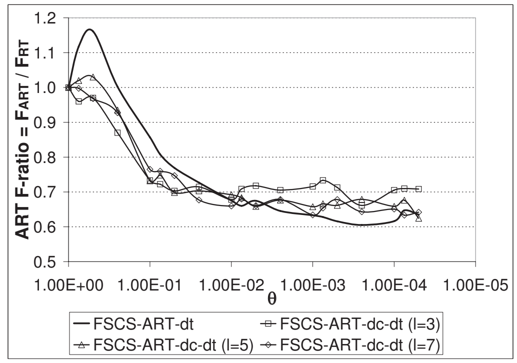
- All 2L-DM-FSCS-ART algorithms outperform FSCS-ART-dt for the cases of high θ and high d_I.

- For 2L-DM-FSCS-ART algorithms with $S_2 = S_{distance}$ (FSCS-ART-dc-dt and FSCS-ART-dp-dt), the failure detection capabilities improve with the increase of l.

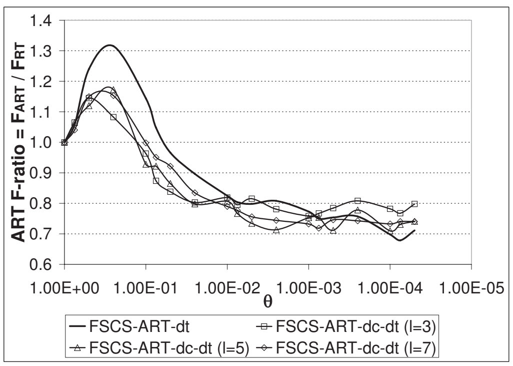
- For 2L-DM-FSCS-ART algorithms with $S_1 = S_{distance}$ (FSCS-ART-dt-



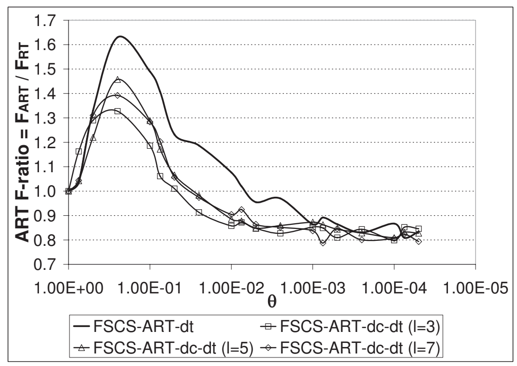
8.a FSCS-ART-dc-dt in 1D space



8.b FSCS-ART-dc-dt in 2D space



8.c FSCS-ART-dc-dt in 3D space

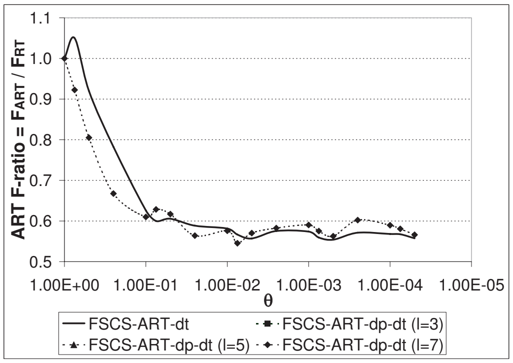


8.d FSCS-ART-dc-dt in 4D space

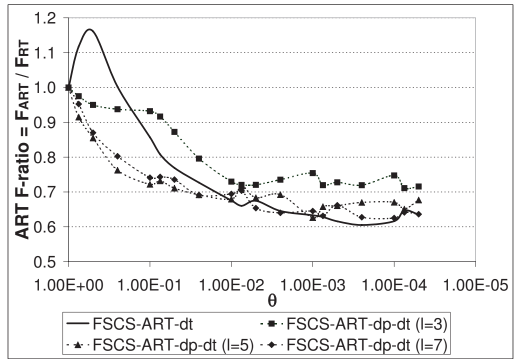
Figure 8: Failure detection capabilities of FSCS-ART-dc-dt

dc and FSCS-ART-dt-dp), the failure detection capabilities improve with the decrease of l.

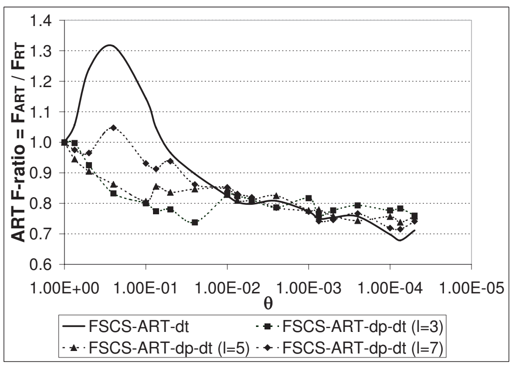
The first observation is consistent with the intuitive expectation. It has been observed by (Chen et al., 2007b,c) that when θ and d_I are high, the original FSCS-ART-dt algorithm does not perform well and does not evenly distribute its test cases in terms of some distribution metrics. Since 2L-DM-FSCS-ART algorithms use these metrics to guide the test case selection process, these algorithms are expected to have better failure detection capabilities than the original FSCS-ART-dt under these situations. For the cases of low d_I or low θ, the original FSCS-ART-dt algorithm performs very well, and it could be observed that as d_I or θ decreases, the F_{ART} of FSCS-ART-dt



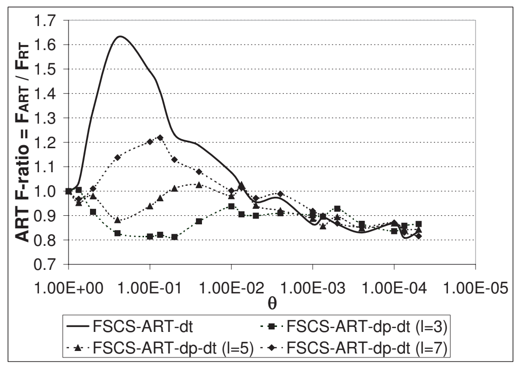
9.a FSCS-ART-dp-dt in 1D space



9.b FSCS-ART-dp-dt in 2D space



9.c FSCS-ART-dp-dt in 3D space

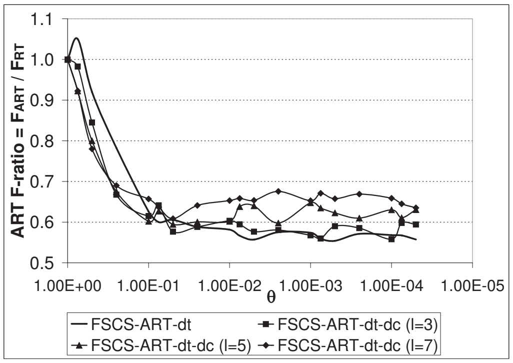


9.d FSCS-ART-dp-dt in 4D space

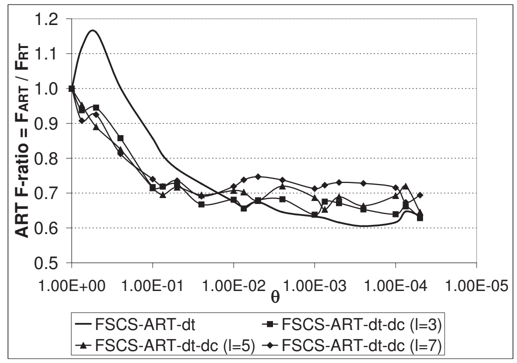
Figure 9: Failure detection capabilities of FSCS-ART-dp-dt

becomes smaller, approaching to the theoretical bound which an optimal testing method can reach without any information about failure locations (Chen and Merkel, 2008). Therefore, it is understandable that 2L-DM-FSCS-ART algorithms do not significantly decrease the F_{ART} when θ is low or d_I is low.

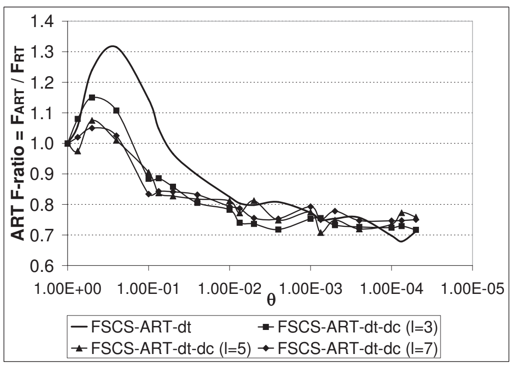
The second and third observations are explained as follows. As mentioned in Section 4, neither $S_{discrepancy}$ nor $S_{dispersion}$ is sufficient to ensure an even spread of test cases. These selection criteria must work together with $S_{distance}$. In FSCS-ART-dc-dt and FSCS-ART-dp-dt algorithms, the next test case is selected from l candidates according to $S_{distance}$. Intuitively speaking, a larger value of l implies that $S_{distance}$ affects performance of these two algorithms more significantly than $S_{discrepancy}$ or $S_{dispersion}$. In FSCS-ART-dt-



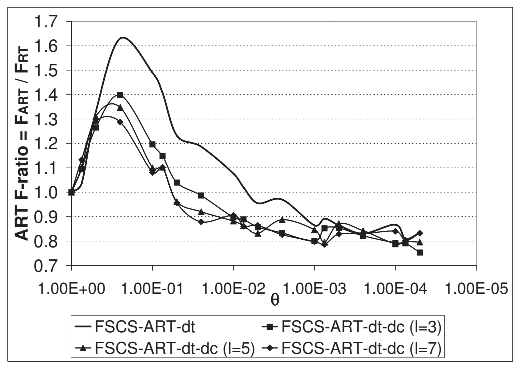
10.a FSCS-ART-dt-dc in 1D space



10.b FSCS-ART-dt-dc in 2D space



10.c FSCS-ART-dt-dc in 3D space



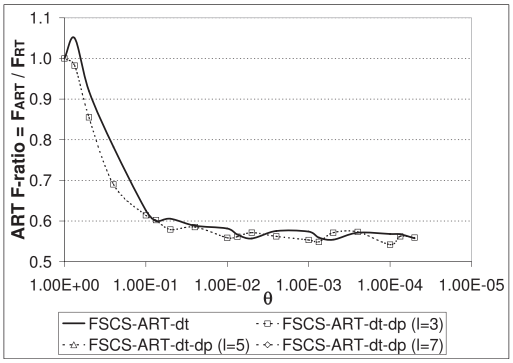
10.d FSCS-ART-dt-dc in 4D space

Figure 10: Failure detection capabilities of FSCS-ART-dt-dc

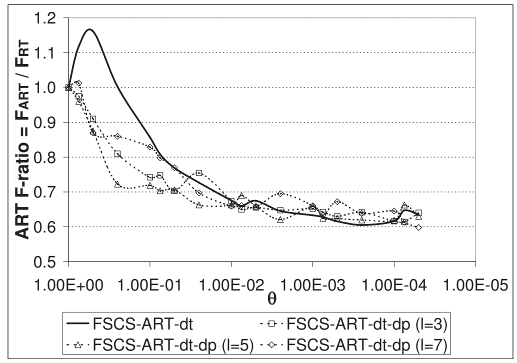
dc and FSCS-ART-dt-dp algorithms, $S_{distance}$ is used to identify l candidates amongst which $S_{discrepancy}$ or $S_{dispersion}$ is going to select one as a test case. Intuitively speaking, in these two algorithms, a smaller l implies that $S_{distance}$ affects the ART performance more significantly than $S_{discrepancy}$ or $S_{dispersion}$.

5.2 DM-ART algorithms with three selection criteria

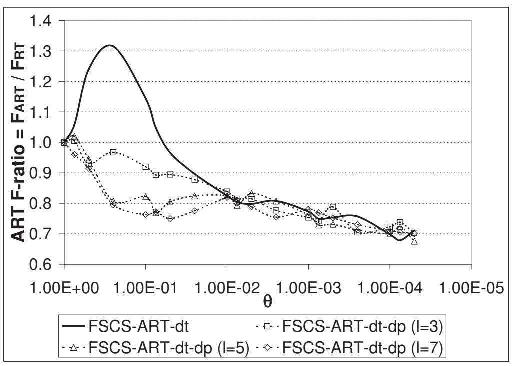
2L-DM-ART algorithms presented in the previous section can only adopt one distribution metric as a test case selection criterion (the other selection criterion is $S_{distance}$ from the original FSCS-ART-dt algorithm). In this section, some more DM-ART algorithms, namely *three-level DM-ART* (3L-DM-ART), are developed to make use of both $S_{discrepancy}$ and $S_{dispersion}$ as



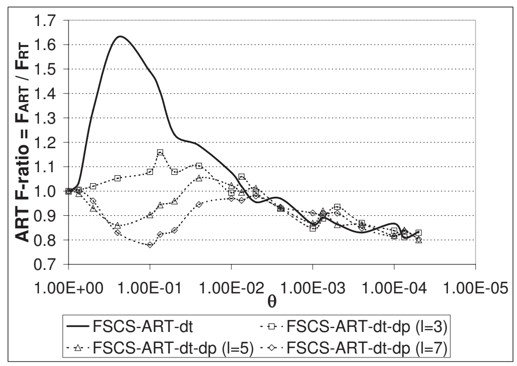
11.a FSCS-ART-dt-dp in 1D space



11.b FSCS-ART-dt-dp in 2D space



11.c FSCS-ART-dt-dp in 3D space



11.d FSCS-ART-dt-dp in 4D space

Figure 11: Failure detection capabilities of FSCS-ART-dt-dp

well as $S_{distance}$ in the test case selection process. Figure 12 gives the detailed algorithm of 3L-DM-FSCS-ART.

As shown in Figure 12, 3L-DM-FSCS-ART will set three test case selection criteria prior to testing (Statement 3 in Figure 12), which are denoted by S_a, S_b and S_c, respectively. Six 3L-DM-FSCS-ART algorithms can be developed, which can be referred to as FSCS-ART-dc-dp-dt (denoting *3L-DM-FSCS-ART with* $S_a = S_{discrepancy}$, $S_b = S_{dispersion}$ *and* $S_c = S_{distance}$), FSCS-ART-dc-dt-dp, FSCS-ART-dp-dc-dt, FSCS-ART-dp-dt-dc, FSCS-ART-dt-dc-dp, and FSCS-ART-dt-dp-dc. Like 2L-DM-FSCS-ART, 3L-DM-FSCS-ART algorithms also require $O(|E|^2)$ time to select $|E|$ test cases.

We conducted some simulations (with settings identical to those given in

1. Input three integers k, g and h, where $k > g > h > 1$.
2. Set $n = 0$ and $E = \{\}$.
3. Set three selection criteria S_a, S_b and S_c, where S_a, S_b, $S_c = S_{discrepancy}$, $S_{dispersion}$, or $S_{distance}$, and $S_a \neq S_b \neq S_c$.
4. Randomly generate a test case t from I, according to uniform distribution.
5. Run the program with t as the test case.
6. **while** (no failure has been revealed)
7. Add t into E, and increment n by 1.
8. Randomly generate k program inputs (candidates) from I, according to uniform distribution, to form a candidate set $C = \{c_1, c_2, \cdots, c_k\}$.
9. Find g best candidates $c'_1, c'_2, \cdots, c'_g$ from C, according to S_a, to form a new candidate set $C' = \{c'_1, c'_2, \cdots, c'_g\}$.
10. Find h best candidates $c''_1, c''_2, \cdots, c''_h$ from C', according to S_b, to form a new candidate set $C'' = \{c''_1, c''_2, \cdots, c''_h\}$.
11. Find the best candidate c''_b from C', according to S_c.
12. Set $t = c''_b$.
13. Run the program with t as the test case.
14. **end_while**
15. Report the detected failure.
16. Exit.

Figure 12: The algorithm of 3L-DM-FSCS-ART

Section 2.3) to evaluate the failure detection capabilities of these 3L-DM-FSCS-ART algorithms. It was found that all 3L-DM-FSCS-ART algorithms have more or less similar failure detection capabilities. We plot the ART F-ratios of FSCS-ART-dc-dt-dp in Figure 13, which also includes the previous simulation results of FSCS-ART-dt, FSCS-ART-dc-dt ($l = 7$), FSCS-ART-dt-dp ($l = 3$) for ease of comparison. In our simulations, the values of g and h for FSCS-ART-dc-dt-dp are set as 7 (similar to the optimal setting for FSCS-ART-dc-dt shown in Section 5.1) and 3 (similar to the optimal setting for FSCS-ART-dt-dp), respectively.

Based on Figure 13, we have the following observations.

- All three DM-ART algorithms outperform FSCS-ART-dt when θ and

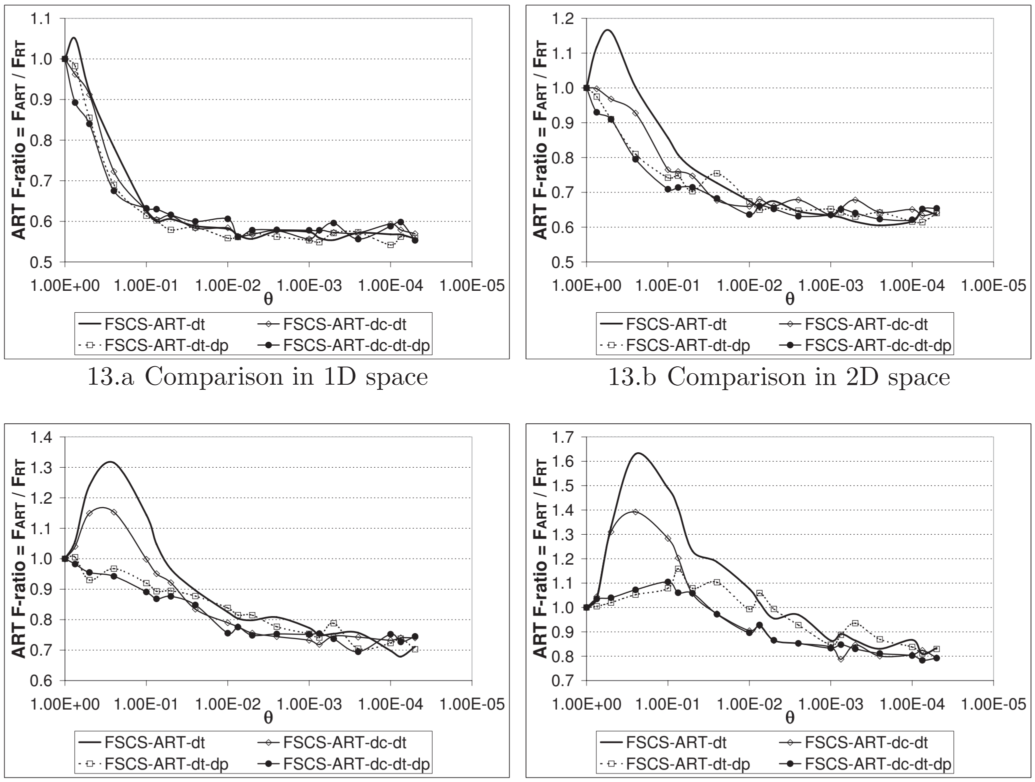


Figure 13: Comparison of Failure detection capabilities for FSCS-ART-dt, FSCS-ART-dc-dt, FSCS-ART-dt-dp, FSCS-ART-dc-dt-dp

d_I are high.

- For 1D and 2D cases, all three DM-ART algorithms have similar failure detection capabilities.

- For 3D and 4D cases,

  - When θ is very small ($\theta < 0.001$), all three DM-ART algorithms have similar performances.

  - When θ is very large ($\theta > 0.1$), FSCS-ART-dt-dp and FSCS-ART-dc-dt-dp have similar performances, which are better than that of FSCS-ART-dc-dt.

- Under other situations ($0.001 < \theta < 0.1$), FSCS-ART-dc-dt and FSCS-ART-dc-dt-dp have similar performances, which are better than that of FSCS-ART-dt-dp.

As shown in Figure 13, among all three investigated DM-ART algorithms, FSCS-ART-dc-dt-dp is the best enhancement to the original FSCS-ART-dt algorithm for various d_I and θ. This is consistent with the intuition that the more criteria are integrated in an ART algorithm, the better performance the algorithm will have. Therefore, in the following sections, we only choose FSCS-ART-dc-dt-dp as the target of our study.

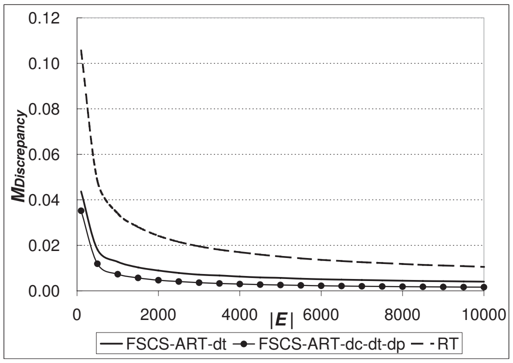
5.3 Test case distributions of DM-ART

More simulations (with settings identical to those given in Section 2.4) were conducted to collect the values of $M_{Discrepancy}$ and $M_{Dispersion}$ for FSCS-ART-dc-dt-dp. The simulations results are reported in Figures 14 and 15, respectively. These figures also include the previous simulation results of FSCS-ART-dt and RT for ease of comparison.

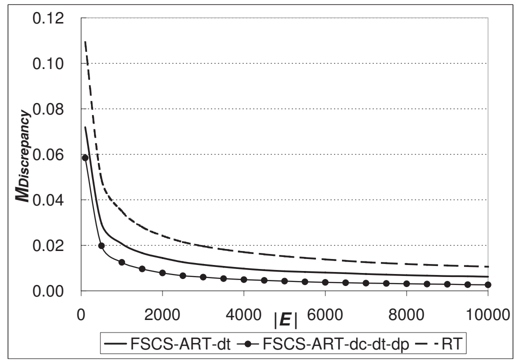
Based on the experimental data, we observe the followings.

- FSCS-ART-dc-dt-dp always has a smaller $M_{Discrepancy}$ than FSCS-ART-dt.
- For 1D and 2D cases, $M_{Dispersion}$ for FSCS-ART-dc-dt-dp is similar to that of FSCS-ART-dt.
- For 3D and 4D cases, FSCS-ART-dc-dt-dp has a marginally smaller $M_{Dispersion}$ than FSCS-ART-dt.

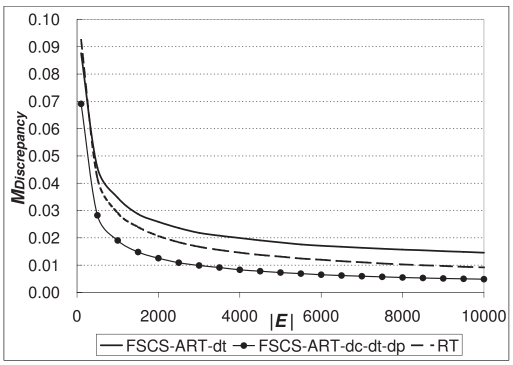
In brief, FSCS-ART-dc-dt-dp spreads test cases more evenly than FSCS-ART-dt, as expected. Such an observation confirms the rationale behind



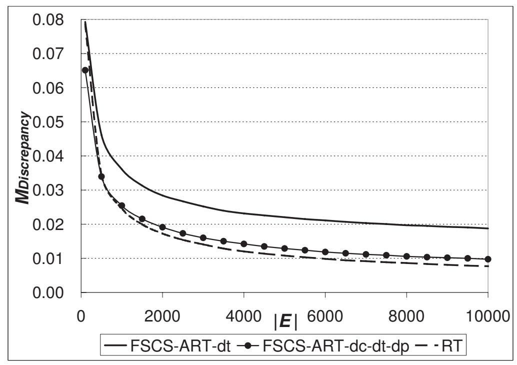
14.a $M_{Discrepancy}$ in 1D space



14.b $M_{Discrepancy}$ in 2D space



14.c $M_{Discrepancy}$ in 3D space



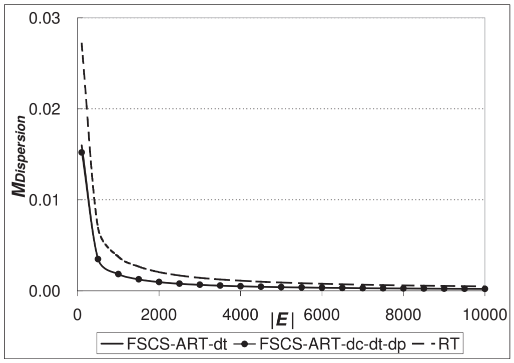
14.d $M_{Discrepancy}$ in 4D space

Figure 14: $M_{Discrepancy}$ of FSCS-ART-dc-dt-dp

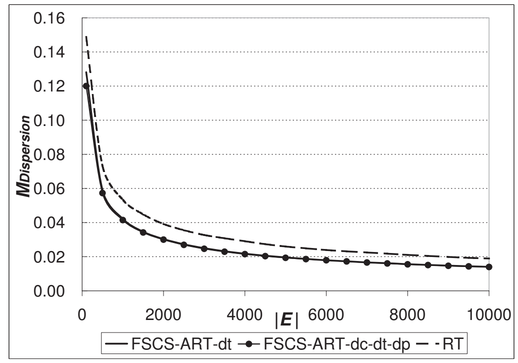
ART that the more evenly test cases are spread, the better failure detection capability an ART algorithm has.

5.4 Effectiveness of DM-ART on real-life programs

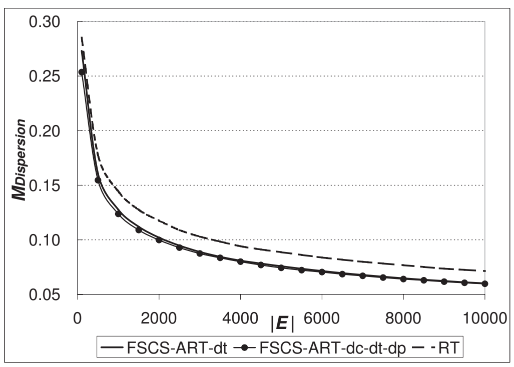
The original FSCS-ART-dt algorithm has been used to test some real-life programs (Chen et al., 2004). These programs, which were published by ACM (1980) and Press et al. (1986), were error-seeded using the technique of mutation (Budd, 1981). For ease of comparison with the previous studies, we also used these error-seeded programs to study the effectiveness of DM-ART. We selected four particular programs as the subject programs, namely *airy*, *bessj*, *plgndr*, and *el2*, whose input domains are 1D, 2D, 3D, and 4D, respectively.



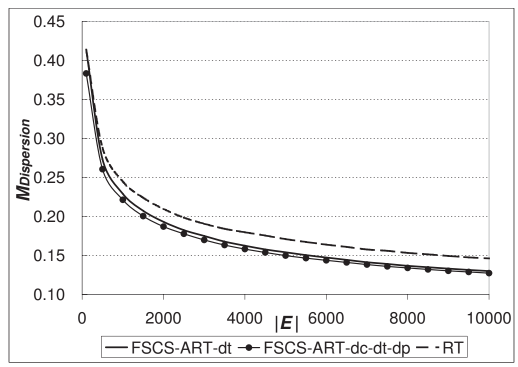
15.a $M_{Dispersion}$ in 1D space



15.b $M_{Dispersion}$ in 2D space



15.c $M_{Dispersion}$ in 3D space



15.d $M_{Dispersion}$ in 4D space

Figure 15: $M_{Dispersion}$ of FSCS-ART-dc-dt-dp

The details of these 4 programs are given in Table 1.

In the simulations conducted in Sections 4.2, 5.1 and 5.2, various values of θ can be selected for study, and the predefined failure regions can reside in any location inside I. However, θ and the location of failure regions in these mutated programs cannot be varied easily to generate a sufficient number of samples to achieve a statistically significant measurement of the failure detection capability.

In this study, we aim to investigate the effectiveness of FSCS-ART-dc-dt-dp under different scenarios (different θ and different locations of failure regions). Therefore, we kept the same seeded errors, but randomly generated 100 different range values for the input domain of each mutated program.

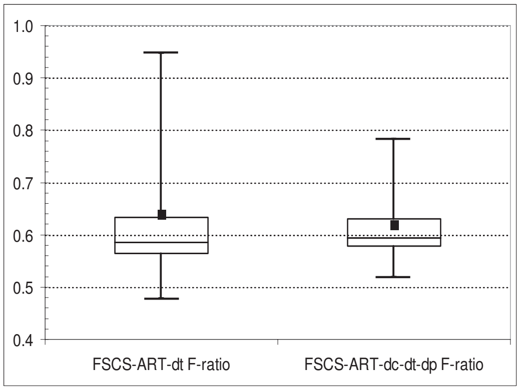
Table 1: Program name, dimension, and seeded errors for each subject program

Program	Dimension	Number of seeded errors			
		AOR	ROR	SVR	CR
airy	1				1
bessj	2	2	1		1
plgndr	3	1	2		2
el2	4	1	3	2	3

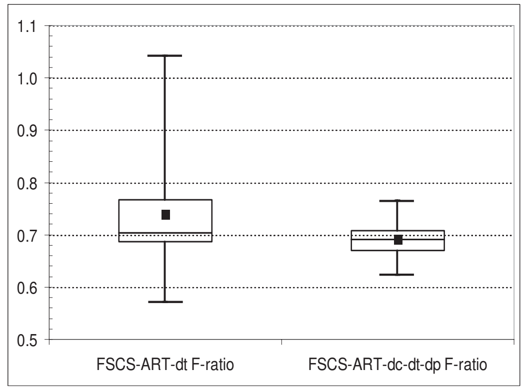
AOR arithmatic operator replacement
ROR relational operator replacement
SVR scalar variable replacement
CR constant replacement

Each randomly selected range value may yield a different θ and a different location of the failure region within the input domain. The shape of the failure region may also be affected. In this way, each subject program can be tested under 100 distinct scenarios.

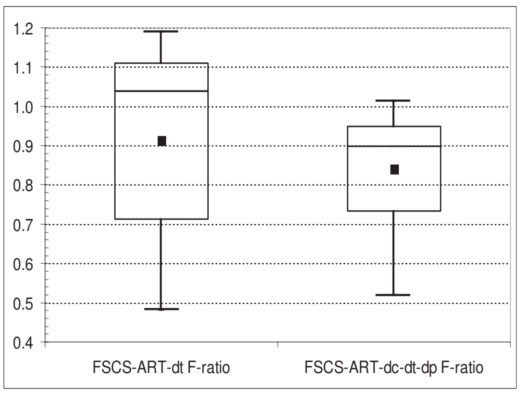
We used both FSCS-ART-dt and FSCS-ART-dc-dt-dp to test the subject programs. The ART F-ratios of FSCS-ART-dt and FSCS-ART-dc-dt-dp on these programs are reported by boxplots in Figure 16. Boxplots (Tukey, 1977), which are widely used in descriptive statistics, provide a convenient way of depicting the distribution of a data set. In a box plot, the first quartile ($x_{.25}$), the median ($x_{.50}$), and the third quartile ($x_{.75}$) of a data set are represented by the bottom edge, the central line, and the top edge of the box, respectively. Upper and lower whiskers (denoted by small horizontal lines outside the box) refer to the maximum and minimum values of a data set, respectively. The whiskers and the box's edges are connected by two vertical lines. Boxplots in Figure 16 also include the mean values of ART F-ratios, denoted by square dots.



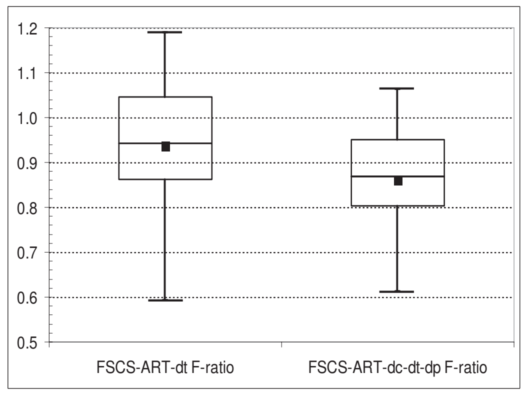
16.a ART F-ratios on *airy*



16.b ART F-ratios on *bessj*



16.c ART F-ratios on *plgndr*



16.d ART F-ratios on *el2*

Figure 16: Comparison of Effectiveness on real-life programs for FSCS-ART-dt and FSCS-ART-dc-dt-dp

Similar to what have been observed in the simulation studies reported in Section 5.2, the failure detection capability of FSCS-ART-dc-dt-dp depends on d_I, but FSCS-ART-dc-dt-dp has a smaller mean value of ART F-ratios than FSCS-ART-dt. The use of boxplots in Figure 16 helps to show that FSCS-ART-dc-dt-dp has a much smaller value range of ART F-ratios than FSCS-ART-dt. Such an observation implies that FSCS-ART-dc-dt-dp is more preferable to FSCS-ART-dt, not only because the former generally has a better failure detection capability than the latter, but also because the former's failure detection capability is less dependent on the value of θ and the location of failure region.

6 Discussion and Conclusion

Adaptive random testing (ART) was proposed to enhance the failure detection capability of random testing (RT) by evenly spreading test cases over the input domain. In many ART algorithms, besides the random generation of the program inputs, some test case selection criteria are additionally used to ensure an even spread of random test cases. Though even spread is intuitively simple, there does not exist a standard definition of even spread, needless to say the existence of a standard measurement for the evenness of test case distribution. Research (Chen et al., 2007b) has been attempted to use various distribution metrics to reflect, if not measure, how evenly an ART algorithm spreads test cases. Previous studies have conclusively shown that some ART algorithms, which are not regarded by certain distribution metrics as evenly spreading their test cases, usually perform poorly. This correlation between test case distribution and failure detection capability has motivated us to develop some new ART algorithms, which apply these distribution metrics, mainly discrepancy and dispersion, as test case selection criteria in ART.

We first studied some algorithms using each of these metrics as the standalone criterion to select test cases in ART. Our simulation results showed that these ART algorithms have poor failure detection capabilities. This is due to the fact that a low discrepancy and a low dispersion are just necessary characteristics of an even spread of test cases, but not vice versa. In fact, simply enforcing test cases to solely satisfy a single criterion leads to certain degrees of uneven test case distribution.

We further investigated the integration of these metrics and the notion of “far apart” in FSCS-ART (that is, keeping test cases as far apart from one another as possible), and proposed a new family of ART algorithms, namely *ART based on distribution metrics* (DM-ART). Two subcategories of DM-ART algorithms, namely 2L-DM-FSCS-ART and 3L-DM-FSCS-ART, were investigated via simulations. The simulation results showed that by keeping the “far apart” notion as the more influential test case selection criterion, some DM-ART algorithms not only spread test cases more evenly, but also have better failure detection capabilities than the original FSCS-ART algorithm. It was also observed that one 3L-DM-FSCS-ART algorithm, namely FSCS-ART-dc-dt-dp, provides the best performance improvement over the original FSCS-ART algorithm among all DM-ART algorithms. An empirical study on FSCS-ART-dc-dt-dp further showed that as compared with the original FSCS-ART algorithm, DM-ART has a failure detection capability less dependent on the failure rate and the location of failure region. In summary, the integration of discrepancy and dispersion with the notion of “far apart” does improve both the evenness of the test case distribution and the failure detection capability.

There are various definitions of discrepancy and dispersion in the literature, and we have only adopted the most commonly used definitions in this study. It is interesting to further investigate the impacts of other definitions of discrepancy and dispersion. Chen et al. (2007b) have pointed out that the ART algorithms under their study may not well satisfy the definitions of some distribution metrics. Restricted random testing, for example, generally has a small dispersion, but a relatively large discrepancy, just like FSCS-ART. Therefore, the innovative approach of this study, that is, adopting test case distribution metrics as test case selection criteria in ART, can be equally applied to enhance other existing ART algorithms.

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