ISSN: 1813-4890

Research on test response compression method based on compression sensing

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Abstract

This paper presents a method to compress the test response data using compressed sensing theory. In this paper, the test response is first grouped according to the different values of sparsity k, aiming to reduce the large number of compatible test vectors in the test response to provide the reduced data for the subsequent sample compression; then by establishing the corresponding sparse random measurement matrix, first multiplying the grouped test vector with the perception matrix, and selecting the vector with the largest absolute value in the result as the result of our final compression. Finally, compare the sparsity k value of the compressed set. If the k value is different, the compressed set can be compatible, and if the same, it can be compressed again. In this paper, DC synthesize the test circuit, generated by ATPG, and VCS. Finally, the sparse random measurement matrix is generated by Matlab, and the final compression result is calculated, and the failure coverage of the test vector is tested by HOPE. The iments show that the compression rate and failure coverage improve compared with other methods.

Keywords

Compression perception, test response compression, block compression, sparse random measurement matrix.

1. Introduction

As an important part of the test optimization method, test compression can effectively reduce the amount of test data and reduce the test time and power consumption. According to the type of test data, test compression can be divided into test incentive compression and test response compression. Generally speaking, test incentive compression is lossless compression, and test response compression is lossy compression. Test response compression is more effective on test data, so it is of important practical significance to conduct research on test response compression. On this basis, with the rapid development and application of digital signal processing, the ability to obtain test vectors is constantly increasing, and the amount of data to be processed is also increasing by at an amazing speed. In recent years, a new theory of compressed sensing (Compressive / Compressed Sensing) has been born. For sparse or compressible signals, this method can properly compress the data while acquiring signals. Its outstanding advantage is that it can reduce the sampled data, save storage space, and contains enough information.

In 2016, Yuan et al. proposed a SoC test data compression scheme based on alternate statistical journey length encoding. This method has the advantages of high compression ratio, low scanning test power consumption, and small extra area cost for on-on-chip system scanning test. However, the fault coverage rate is not mentioned in this scheme, and there is still room for improvement. In 2017, Au-Yeung, Enrico. They constructed a new class of random matrix. In the scheme, a non-random matrix is constructed, and then its matrix is decomposed into

ISSN: 1813-4890

multiple submatrix, using these submatrix and Bernoulli random matrix to construct the final matrix. Therefore, this new type of random matrix. Although the compression rate of this scheme is high, the hardware cost and power consumption are not mentioned, which remains to be verified by experiments. In 2017, Lu Cunbo et al. proposed a deterministic measurement matrix construction algorithm based on multi-dimensional pseudorandomized sequence. The algorithm is able to produce binary pseudorandom sequences and transform them numerically to obtain the corresponding set of bipolar pseudorandom sequences, which are reconstructed into a deterministic measurement matrix. In 2021, Yang Junpo and Liu Wenyuan constructed a deterministic measurement matrix by using the bipolar matrix of the binary pseudo-random sequence. Simulation experiments show that in the same condition of the compressed sensing algorithm, the two schemes constructed matrix are implemented by the linear feedback shift register structure, are easy to implement hardware, but the two schemes for a multi-dimensional random sequence matrix, a two-dimensional random sequence structure matrix, which is simpler than the former is easier to operate, and both are deterministic matrix, randomness is bad. In 2018, Bhandari et al. proposed a vector generation technique. This technique uses partial fixed bit sequence and bit insertion techniques, and the simulation results show that the method can reduce the test power consumption while improving the failure coverage compared with LFSR based BIST. In 2019, Dilp et al. used reseeding LFSR technique to generate a pseudo-random test vector for the tested circuit. This technology has low power consumption and low amount of test data, with an average failure coverage of about 90%. In 2020, Lokesh Sivanandam et al. proposed an encoding compression technique is proposed by using the order of power conversion and then using the Huffman encoding technique. This method not only improves the compression rate of the test data, but also reduces the test power consumption of the circuit. The proposed method in the paper maintains a small area overhead while also reducing the test time.

In view of the test data compression, domestic and foreign scholars have done a lot of research to improve the compression efficiency, reduce the test time and other aspects, and have achieved good results. According to the above conditions, combined with the characteristics of random observation matrix and deterministic observation matrix, as well as the conditions conducive to the hardware implementation, this paper explores and innovates in these aspects, and proposes the test response compression design with sparse random matrix. By comparing the performance of a variety of measurement matrix, the final using sparse random matrix to compress the test response data, because the test response data is too large and there is a great correlation between the vector, so the first test response data block processing, data compatibility before compression, this scheme can improve the efficiency of data compression and can improve the data compression rate. The flow chart of the overall scheme is shown in Figure 1.

2. Compression sensing process

2.1. Perception process

In this paper, through the test circuit, the test response is the perception data we need. However, if the amount of perceptual data affects data analysis, it will waste a lot of time to compress. Therefore, we will preprocess the original test response data and process the compatible vectors in the data into a sparse test response vector. Figure 2 below shows the compressed sensing flowchart.

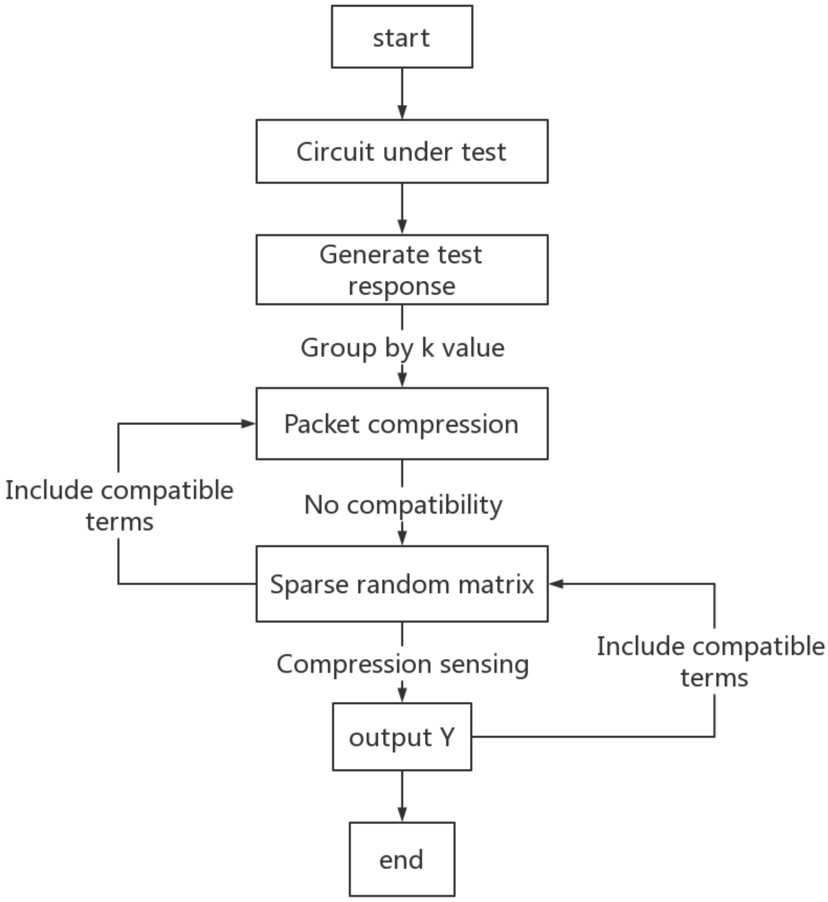

Fig. 1 The flow chart of the overall scheme

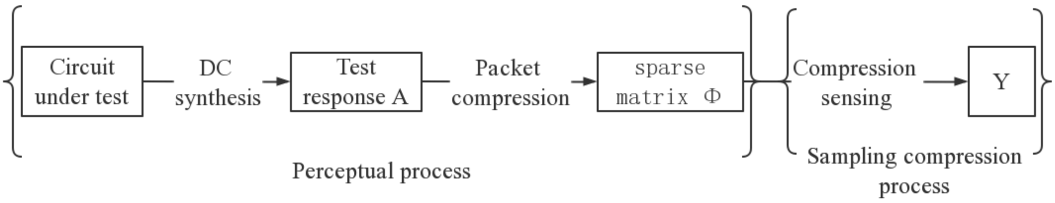

Fig. 2 The compressed sensing flowchart

We through the test circuit DC synthesis generated after the original test response A group compression, test vector generally composed of 0,1 and X, X called irrelevant bits, the number of irrelevant bits in large-scale circuit is very much, generally above 70%, because there are A large number of irrelevant bits in the test vector, so test vector between compatibility, different vector ability to detect fault, if two vectors compatible, then their failure ability, can combine multiple test vector, so as to reduce the test set size. As the test set size decreases, the compression rate of the data also increases.

This paper defines the compatibility relationship as: we call two lines, lines fan out to the corresponding scan chain to complete the test. For the test set with unbalanced bit distribution, if the test vector is directly arranged according to the multi-scan chain structure and the pattern compatibility, the compression effect is not good. If the same test set is divided into 2 to 3 groups based on the number of identical compatible items between the test vectors, and then separately pattern compatible, the overall compression effect is much higher.

ISSN: 1813-4890

The grouping method of this in this paper is as follows: after the test vector is arranged according to multiple scans, first find out the pattern compatibility terms for each vector, that is, the compatibility relationship between the rows within the vector, and then count the number of compatible terms of the same between the vector, which is calculated from the Hemming distance. Let k be the boundary value of the same number of compatible items, and the value of k is determined by the following algorithm: within the value range of k, select the value of k for each one. The vectors with the same number of compatible terms (or equal) k between the test set are divided into one group, and the remaining vectors are another group. To further improve the compression rate, the test set can be divided into three groups according to the grouping method mentioned above, but the decompression structure and control logic will also become complicated. There is a trade-off between the increased compression rate and the hardware cost of grouping. Based on this trade-off, the test set is divided into 2 groups when the number of multiple scan chains of the tested circuit is less than or equal to 32, and the test set is more than 32. The test vector grouping compatibility process is shown in Figure Figure 3.

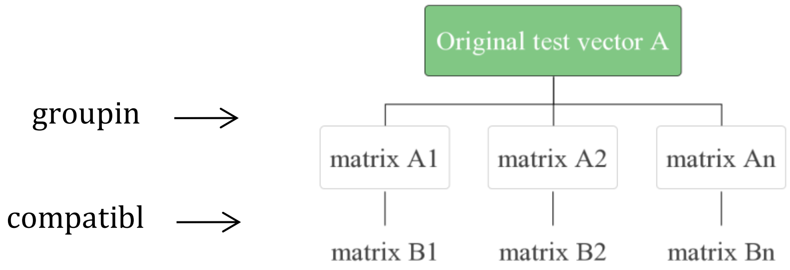

Fig. 3 The test vector grouping compatibility process

2.2. Construction of the perception matrix

The common response compression is to convert m×n data into p×q vector data C, and the relationship between the data is that m is greater than p, and n is greater than q. The transformation function is used to set C=Φ(D) for analysis and inference. In the compressed sensing method, we can represent the sparse mapping matrix of M×N dimension by Φ; besides, X represents the original test response vector of m×n dimension, which is sparse and sparse value of k; Y represents the M-dimensional observation signal, which is the compressed test vector. The compression process is simply Y by the known X and Φ in Y=ΦX. In this model, if the original signal X satisfies certain sparse characteristics, it can be compressed into a very small vector space through the action of the sparse mapping matrix Φ, that is, the number of rows of Y is much smaller than X, which also reflects the core idea of sparse theory: high-dimensional signals are described by low-dimensional signals.

During signal sampling, the following linear relationship exists between the original vector X, the measurement matrix Φ and the observed signal Y:

$$Y = \Phi X \tag{1}$$

If each row of the perception matrix Φ is regarded as a sensor, and multiplying with the signal X can obtain the partial information Y (M≤N) of the signal, And is an observation of the compressibility. Since K<M<N, Y=ΦX is an underdetermined equation whose solution should be with or without an array. Therefore, the constraint isometry (RIP) is proposed for the selection of the measurement matrix Φ. An equivalence case of the RIP principle is that the measured matrix X is not correlated with the sparse matrix Φ, and the RIP will be explained in detail later.

If there is A measured matrix A, satisfying the A= (A_1, A_2, A_3,..., A_N) RMN, the correlation μ (A) is defined as follows:

$$\mu(A)=\max_{1\le i\ne j\le N}\frac{\left|\langle\alpha_i,\alpha_j\rangle\right|}{\|\alpha_i\|_2\bullet\|\alpha_j\|_2} \tag{2}$$

And, $\langle\alpha_i,\alpha_j\rangle=\alpha_i^T\alpha_j$ represents the vector inner product.

According to the definition of compressed sensing correlation, the sparsity k is the number of non-0 elements of the pointing quantity, such as x= (0,1,0,1,0,0,0), and the value of k is 2. The more 0 in the test vector, the sparser. When we pre-process the raw test response data, the k value in the test vector needs to meet:

$$k<\frac{1}{2}\left(1+\frac{1}{\mu(A)}\right) \tag{3}$$

When n≫m in matrix A, the minimum value of $\mu(A)$ can be calculated:

$\mu(A)_{\min}=\sqrt{\frac{n-m}{m(n-1)}}\approx\frac{1}{\sqrt{m}}$, then the k value can be:

$$k<\frac{1}{2}\left(1+\frac{1}{\mu(A)}\right)=\frac{1}{2}\left(1+\sqrt{\frac{m(n-1)}{n-m}}\right)\approx\frac{1}{2}\left(1+\sqrt{m}\right) \tag{4}$$

When m≫n in matrix A, the minimum value of $\mu(A)$ can be calculated:

$\mu(A)_{\min}=\sqrt{\frac{m-n}{m(n-1)}}\approx\frac{1}{\sqrt{n}}$, then the k value can be:

$$k<\frac{1}{2}\left(1+\frac{1}{\mu(A)}\right)=\frac{1}{2}\left(1+\sqrt{\frac{m(n-1)}{m-n}}\right)\approx\frac{1}{2}\left(1+\sqrt{n}\right) \tag{5}$$

According to the above equation (3), reducing μ(A) will increase the sparsity k of the reconstructed signal, so that the compression effect is better when the test vector is compressed. Therefore, in order to achieve the compression signal with high compression rate, it is required to construct the measurement matrix A and reduce its correlation μ(A) as much as possible. In order to ensure that the observation matrix does not place two different k-sparse signals in the same set, it also ensures that the failure problem will not occur, and the compression quality is guaranteed. The so-called RIP is similar to the mine distance in our SoC. The following data will be processed according to the size of the mine distance.

This paper proposes that the sparse random measurement matrix in compressed sensing is applied to the test vector compression. The matrix is defined as the matrix: if the number of elements with 0 is much more than the number of non-0 elements, and the distribution of non-0 elements is not regular, the matrix is called sparse matrix. The characteristics of its sparse matrix are shown as follows:

The number of non-zero elements of the sparse matrix is much smaller than the number of zero elements, and the distribution of these non-zero elements is not regular.

Sparse factor is the proportional case of non-zero elements used to describe the sparse matrix. Let there be t non-zero elements in a sparse matrix A of n×m, then the calculation formula of the sparse factor k is as follows: k=t/(n×m) (when this value is less than or equal to 0.5, it can be considered as a sparse matrix).

In this paper, X is an n-dimensional feature vector; D is a standardized basic matrix, composed of basic atoms of elements, also called dictionary; X can be linearly composed of D and a small number of atoms, its representation coefficient is sparse.as follows:

$$(X)=(d_1 \quad d_2 \quad \cdots \quad d_n)\times\begin{pmatrix}\alpha_1\\ \alpha_2\\ \vdots\\ \alpha_n\end{pmatrix} \tag{6}$$

Among $X\in R^m$， $D\in R^{m\times n}$， $\alpha\in R^n$ are a sparse signal, and m<n. From the knowledge of linear algebras, the sparse coefficients have an infinite number of solutions. According to the sparsity condition, we can pick out the solutions with the least non-0 elements among all the feasible solutions, that is, to satisfy the sparsity. The following mathematical model is then obtained:

$$\min \| x - D\alpha \|_2^2 \text{ s.t.} \| \alpha \|_0 = y \tag{7}$$

From the above equation, we require that the solution is the minimum two-norm of x-Dα when the sparsity signal α is close to 0. Therefore, in this paper, a sparse random matrix Φ of size M×N is constructed, where the number of elements in each column is not zero is d. The form of the constructed sparse random matrix Φ is shown in Equation (9). In equation (9), the independent variables $a_{i,j}$, i=1,..., M, j=1,..., N satisfy the probability distribution p(x) of equation (8).

$$\Phi_{i,j}=\begin{Bmatrix}\frac{+1}{\sqrt{q}} & p=\frac{q}{2}\\ 0 & p=1-q\\ \frac{-1}{\sqrt{q}} & p=\frac{q}{2}\end{Bmatrix},\ q\in(0,1) \tag{8}$$

$$\phi=\frac{1}{\sqrt{d}}\begin{pmatrix}a_{1,1} & a_{1,2} & \cdots & a_{1,N}\\ a_{2,1} & a_{2,2} & \cdots & a_{2,N}\\ \vdots & \vdots & & \cdots\\ a_{M,1} & a_{M,2} & \cdots & a_{M,N}\end{pmatrix} \tag{9}$$

In this paper, we implement the generation of a random sparse matrix via matlab. This matrix is passed by first generating a full 0 matrix Φ of size M×N, and M<N. Then for each column of the matrix Φ, randomly selected d positions and then the selected position over 1, here d<M. Each column of the sparse random measurement matrix has only d non-0 elements, simple structure and easy to construct and save in practice. When selecting the parameter value, it is decided according to the test matrix generated after the test response group compression, where the value of M is less than the value of N, and the value of d is less than the value of M, d<M<N. Where the value of N is determined by the number of output ports in the tested circuit; the value of d is determined by the value of sparsity k in the matrix A generated by the test vector, taking the progressive upper bound value of k, namely d=O (k); the value of M is $M=O\left(\frac{N}{d}\right)$.

2.3. Sampling and compression process

We multiplied the test vector matrix by the perceptual random matrix, and obtained the base vector corresponding to the vector where the absolute value of all coefficients was the largest in the coefficient vector, and then compressed the selected base vector to the final test response we needed. Then we can choose a matrix $A=[A_1^T,\ A_2^T,\ A_3^T,\cdots,\ A_n^T]$,Where $A_n^T=[a_{0,n} \quad a_{1,n} \quad \cdots \quad \cdots \quad a_{m-1,n} \quad a_{m,n}]$ is the test response, and $\{m,n\}\in\{1,2,3,\cdots,n\}$.Among them,

$Y = \phi A_n$,Y is the column vector An in the signal set matrix A that we collected and it is projected to the perception matrix Φ (namely sparse random matrix) to obtain the final test response set, finally $Y = [y_1 \quad y_2 \quad \cdots \quad \cdots \quad y_{m-1} \quad y_m]$.We take the base vector corresponding to the ym value with the largest absolute value in the set Y as the test vector that we finally seek. The calculation procedure is shown below.

$$A_{m\times n} = \begin{bmatrix} a_{0,0} & a_{0,1} & \cdots & a_{0,n-1} & a_{0,n} \\ a_{1,0} & a_{1,1} & \cdots & a_{1,n-1} & a_{1,n} \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ a_{m-1,0} & a_{m-1,1} & \cdots & a_{m-1,n-1} & a_{m-1,n} \\ a_{m,0} & a_{m,1} & \cdots & a_{m,n-1} & a_{m,n} \end{bmatrix} \quad (10)$$

$$\phi_{m\times n} = \begin{bmatrix} 0 & 0 & \cdots & 0 & 1 \\ 1 & 0 & \cdots & 0 & \varphi_{1,N} \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & \varphi_{M-1,N} \\ 0 & 0 & \cdots & 1 & \varphi_{M,N} \end{bmatrix} \quad (11)$$

$$Y = \begin{bmatrix} a_{0,0} & a_{0,1} & \cdots & a_{0,n-1} & a_{0,n} \\ a_{1,0} & a_{1,1} & \cdots & a_{1,n-1} & a_{1,n} \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ a_{m-1,0} & a_{m-1,1} & \cdots & a_{m-1,n-1} & a_{m-1,n} \\ a_{m,0} & a_{m,1} & \cdots & a_{m,n-1} & a_{m,n} \end{bmatrix} \times \begin{bmatrix} 1 \\ \varphi_{1,N} \\ \vdots \\ \varphi_{M-1,N} \\ \varphi_{M,N} \end{bmatrix} = [y_1 \quad y_2 \quad \cdots \quad y_{m-1} \quad y_m] \quad (12)$$

In this paper, the method of compressed perception is adopted to compress the test response, and then compress the perception first. The perception process is the process of processing the test circuit, so that the signal is perceived, and then the perceived signal is compressed through the perception matrix Φ.

2.4. Compression, confusion and fault coverage analysis

The test response compression does not necessarily have to ensure the failure coverage rate, as long as the characteristic value of the response compression is different from the expected result. The impaired nature of the confusion rate and the test response compression may cause the loss of the original data, resulting in some cases where the fault existing in the circuit cannot be detected, and the resulting characteristic value after the fault compression is the same. Confusion is a problem that needs to be solved in response compression. Confusion means that the response data with wrong bits is exactly the same as the compression results after the correct response data is compressed, so that the tester can misunderstand the wrong response results as correct, and the less the confusion occurs in the test, the better.

HOPE failure simulation has many functions, which can be used to calculate the failure coverage of a given failure model, auxiliary test generation and test set compression, etc. Its inputs include circuit networks and test vector sets. The circuit description form accepted by HOPE is the network table file, which is basically consistent with the reference circuit table form of the network table, that is, the circuit structure is described in the circuit description language, including the original input transmission number, gate number and circuit structure of the circuit.

In this method, the confusion rate of the compression circuit is calculated as follows:

$$P_{confound} = \frac{(m\times n)\text{ Number of non - m - bit elements in bit space} - 1}{(m\times n)\text{ Number of elements in bit space}} = \frac{2^{mn}-1}{2^{mn}} \approx 2^{-m} \quad (13)$$

The most commonly used compression ratio is selected to measure the compression ability of the test vector compression method based on the calibration matrix, which is defined as:

$$R = \frac{\text{Number of output data ends}}{\text{Number of input data ends}}$$

Because HOPE needs to be compiled in a Linux environment, this article uses the synophys software to run in a Linux environment. We enter a series of command-line instructions to obtain the required fault simulation results. The fault simulation interface gives the circuit structure, program running time and fault coverage rate.

3. Experimental results and analysis

Table 1 lists the comparison of the compression rate of this method and the direct compression method. It can be seen in the table that the compression method proposed in this paper can get better compression effect compared with the direct compression method, and the compression rate is generally increased by 20%. The s38417 circuit has improved the most. But the compression rate of the s5378 circuit is slightly lower than the overall compression rate. This is because the test vector data of the tested circuit itself is relatively small, resulting in reduced operability in data compression, so the compression rate is lower than that of other circuits. In addition, the test vector set is compatible in advance, while the s13207 circuit has less compressed vectors in the processing, so the scale of the compressed vector number is not reduced much after the transformation analysis, so the compression rate is low, mainly because of the s13207 test vectors are more. However, this method is relatively balanced in the analysis of compression rate and failure coverage rate, and is not a solution to ignore the other.

Table 1 Encoding compression radio comparison

Circuit name	Direct compression(%)	This method compresses(%)
s5378	47.98	88.34
s9234	43.61	96.20
s13207	81.31	91.89
s15850	66.21	90.77
s38417	43.27	96.30
s38584	60.93	95.29

Table 2 Fault coverage comparison

Circuit name	Fault coverage(%)		
	Hadamard	Bernoulli	This method
s5378	67.3	71.4	99.1
s9234	46.7	52.3	93.5
s13207	74.5	69.8	98.5
s15850	72.9	84.6	96.7
s38417	43.3	81.3	97.6
s38584	60.9	73.6	95.9

4. Conclusion

In order to improve the compression rate of test response data, this paper proposes a compression method of test response based on compression perception. Firstly, this method compress the test response data, mainly to eliminate the excess compatible vectors, reduce the test data set and provide favorable conditions for subsequent sampling compression, then multiply the constructed sparse random matrix and compress the test set based on the transformed results. This method has improved compression rate and failure coverage compared with other methods.

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