Comparison of Wafer-level Spatial I_{DDQ} Estimation Methods: NNR versus NCR

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Abstract

Extending the useful life of I_{DDQ} test to deep submicron technologies has been a topic of interest in recent years. I_{DDQ} test loses its effectiveness as the signal to noise ratio degrades due to rising background current and fault-free I_{DDQ} variance. Defect detection using I_{DDQ} test requires separation of deterministic sources of variation from defective current. Several methods that use deterministic variation in I_{DDQ} at the wafer level for estimating fault-free I_{DDQ} of a chip are proposed. This paper compares two such methods: Nearest Neighbor Residual (NNR) and Neighbor Current Ratio (NCR). These methods are evaluated using industrial test data for a recent technology.

Keywords: I_{DDQ} testing, spatial correlation, NNR, NCR

1. Introduction

Extending the life of I_{DDQ} test to deep sub-micron (DSM) technology by improving its sensitivity is a topic of research in recent years [1][2]. Several methods that use wafer-level I_{DDQ} test data for estimating fault-free I_{DDQ}, and, in turn, for outlier identification have been proposed [3][4][5]. Two data statistical post-processing (SPP[1]) methods called Nearest Neighbor Residual (NNR) and Neighbor Current Ratio (NCR) have been proposed. This paper investigates whether one is better than the other and under what conditions, to observe whether the findings can be used to improve SPP-based methods. A general review of I_{DDQ} test challenges and methods can be found elsewhere [6][7]. We review NNR [3][8] and NCR methods [5] in Section 2. A variation of NCR is suggested. Section 3 describes our analysis method. Section 4 describes the results obtained from a 130 nm technology data[2]. Section 5 presents conclusions.

2. Review of NNR and NCR Methods

Both NNR and NCR are based on the observation that a part of the variation in I_{DDQ} of adjacent chips on a wafer is deterministic in nature. If the deterministic variation can be separated out, the remaining variation is most likely due to a defect. This premise can be used for identifying outlier dice at the wafer level. By estimating deterministic variance more accurately, outlier screening can be improved. The two approaches are described next.

2.1 Nearest Neighborhood Residual (NNR)

The NNR-based approach estimates intrinsic I_{DDQ} of a die using neighboring dice I_{DDQ} data. It is based on the assumption that the intrinsic I_{DDQ} is relatively independent of the test vector and is a function of the die position on the wafer. The estimate of intrinsic I_{DDQ} for the die at position (x,y) is obtained by averaging I_{DDQ} over all test vectors N_v.

$$E(I_{DDQ}) = \overline{I_{DDQ}}_{(x,y)} = \frac{1}{N_v}\sum_{i=1}^{N_v} I_{DDQ(i)(x,y)} \qquad (1)$$

The goal of the NNR method is to reduce the variance in fault-free I_{DDQ} data. The total I_{DDQ} variation (σ^2_{iddq}) is composed of a vector-dependent component (σ^2_{vector}) and a wafer-level component (σ^2_{wafer}). Since vector-to-vector variation is averaged out by Eq. (1), the variance in distribution of the mean I_{DDQ} is equal to that from process variation (σ^2_{wafer}). Variance reduction can be achieved if a new value for process-induced variation smaller than σ^2_{wafer} is found. NNR uses I_{DDQ} variance in the local neighborhood ($\sigma^2_{neighborhood}$) to replace σ^2_{wafer}. Variance reduction is possible if the following equation is satisfied:

$$\frac{\sigma^2_{neighborhood}}{\sigma^2_{vector} + \sigma^2_{wafer}} < 1 \qquad (2)$$

The neighborhood as defined by the NNR method consists of neighboring die of the reference die (X_rY_r) whose I_{DDQ} is to be estimated. The neighboring dice are divided among different groups based on their distance from the reference die. Here, distance between any two die is the straight line connecting their centers. Each die is considered one unit wide and one unit long. The first five groups and their distances are shown in Table 1 and marked in Figure 1. The reference die is shaded and marked as X_rY_r. The third column in Table 1 represents the horizontal and

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[1] SPP is trademark of LSI Logic Corporation.
[2] This data comes from Texas Instruments. The conclusions drawn are our own and do not necessarily represent the views of TI.

vertical distance in terms of number of die (units) from X_rY_r.

The NNR method relies on correlation between neighboring die to obtain an estimate of fault-free I_{DDQ} for die at X_rY_r. This is called the Nearest Neighbor Estimate (NNE). To obtain the NNE, at least k dice in the local neighborhood are considered, with a typical value of k being 8. The median of average I_{DDQ} values for these k dice is used as the NNE for the reference die X_rY_r. While considering k neighboring dice, if sufficient dice are not available in a group, all available dice from the succeeding group are added. For example, if data is available for only two dice from group 2 (out of 4 possible), all available dice from group 3 (maximum 4) will be considered. Thus, in this case, a total of 8 dice will be considered; two each from groups 1 and 2, and 4 from group 3. This process continues until the lower bound on the user specified value (k) is met. The median of the average values for these k estimators gives the NNE. The NNR is the difference between the actual value and NNE.

$$NNR_{x,y} = \overline{IDDQ}_{x,y} - NNE_{x,y} \qquad (3)$$

An example of the variance reduction achieved by the NNR method is shown in Figure 3. It shows histograms of the actual I_{DDQ} values and NNE obtained by NNR method for chips from a single wafer. The scale on the X-axis is the same for both figures. To protect sensitive data, the X-coordinates and the mean values are not shown. For each chip, I_{DDQ} was obtained by averaging 10 readings. NNE was obtained by considering all available neighboring chips from group 1 and group 2. In this figure, data for 501 chips is shown. Due to median value selection, NNE is less sensitive to outliers and has smaller variance than the original data.

Table 1. Neighborhood Distances from X_rY_r.

Group	Distance (n)	Vector
1	1	(±1,0), (0, ±1)
2	$\sqrt{2}$	(1,1)
3	2	(±2,0), (0, ±2)
4	$\sqrt{5}$	(±2, ±1), (±1, ±2)
5	$\sqrt{8}$	(±2, ±2)

5	4	3	4	5
4	2	1	2	4
3	1	X_rY_r	1	3
4	2	1	2	4
5	4	3	4	5

Figure 1. NNR Neighborhood Group Definition.

2.2 Neighbor Current Ratio (NCR)

The NCR-based method also relies on wafer-level spatial correlation between neighboring dice on a wafer. The neighborhood considered for NCR, however, is limited to eight adjacent dice. Referring to Figure 1, this corresponds to dice from groups 1 and 2 only. NCR is the ratio of I_{DDQ} values of the reference die (X_rY_r) and neighboring die for identical vectors. For k neighbors and n vectors, a total of $n{\cdot}k$ NCR values can be obtained. The conventional definition of NCR considers only the maximum of these values [9]. This value essentially represents the maximum deviation of reference die I_{DDQ} from the "normal" I_{DDQ} variation in the neighborhood. Thus,

$$NCR = \max\left(\frac{IDDQ^i_{xr,yr}}{IDDQ^i_k}\right) \forall k, \forall i;\ i = 1\ to\ n \qquad (4)$$

where i is the vector number and k is the neighboring die.

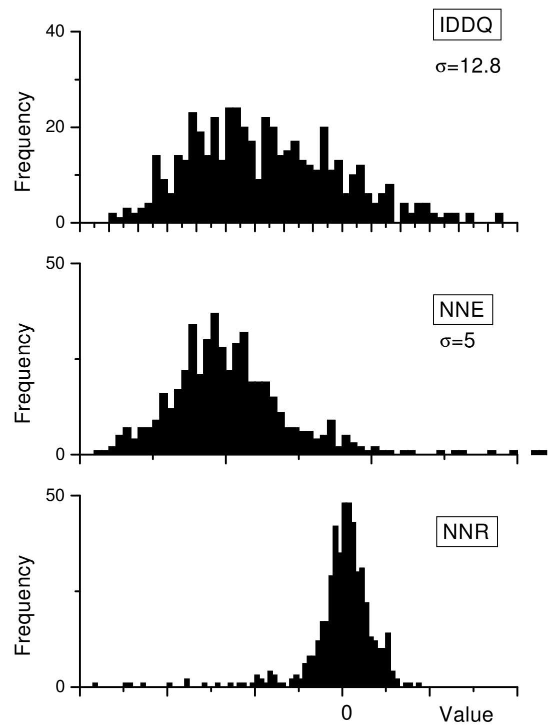

Figure 2. Variance Reduction Obtained by NNE.

Both NNR and NCR have some characteristics in common. Both methods rely on wafer-level correlation between neighboring dice. The definition of neighborhood need not necessarily be limited to physically adjacent dice on the wafer. It can be extended to dice that are highly correlated to the reference die due to manufacturing conditions [10]. In the extreme case, the most "influential" neighbors need not be from the same wafer [11]. In the present study, however, we only consider neighbors in the vicinity as shown in Figure 1. It may be noted that sensitivities and accuracies of both NNR and NCR schemes are limited due to defect clustering [12]

We can also use mean NCR – a value obtained by dividing the mean I_{DDQ} of the reference die by the mean I_{DDQ} of neighboring die – for comparison. In this case, out of k possible NCR values, the maximum NCR is used as the mean NCR. Thus,

$$meanNCR = \max\left(\frac{meanIDDQ_{xr,yr}}{meanIDDQ_k}\right)\forall k \qquad (5)$$

Although the mean NCR is a less sensitive method for outlier detection, it is somewhat similar to the NNR approach, and offers a better variance reduction alternative. This is illustrated with the help of Figure 3. It shows histograms for NNR, NCR and mean NCR values. Ideally, the mean NNR is zero. Note that the NCR value defined in Eq. (4) has higher probability of being more than 1. This means that NCR can be used for more effective screening of hard-to-detect defects. It can be used to improve confidence for screening marginal outlier chips near the core population.

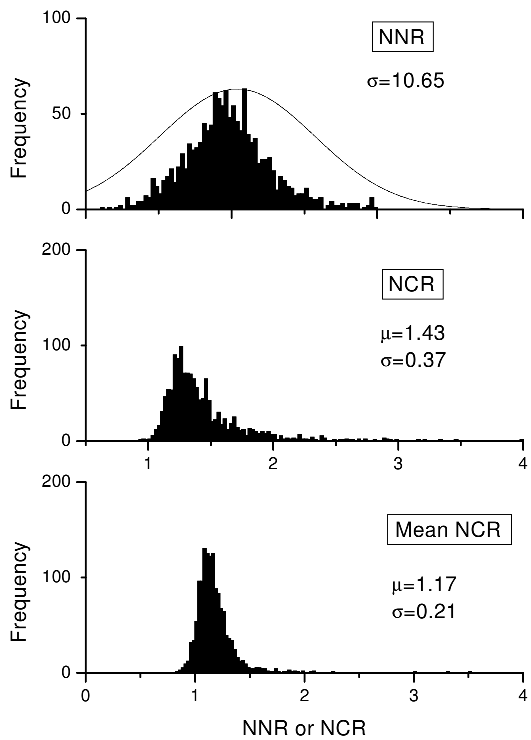

Figure 3. Comparison of Variance Reduction by NNR, NCR and Mean NCR (single wafer).

3. NNR and NCR Comparison

Both NNR and NCR methods rely on wafer-level spatial correlation. In order to compare NNR and NCR, we use the same neighborhood definition as NNR as described in Section 2. For each die position, the average I_{DDQ} is obtained by considering all vectors. Neighbors from different groups are added until the minimum number of neighbors (k) is 8. Since all chips from a group are added to achieve this, in some cases the total number of chips considered can be more than 8. The NCR and mean NCR values are computed using Eq. (4) and (5) using the same neighborhood chips considered for NNR.

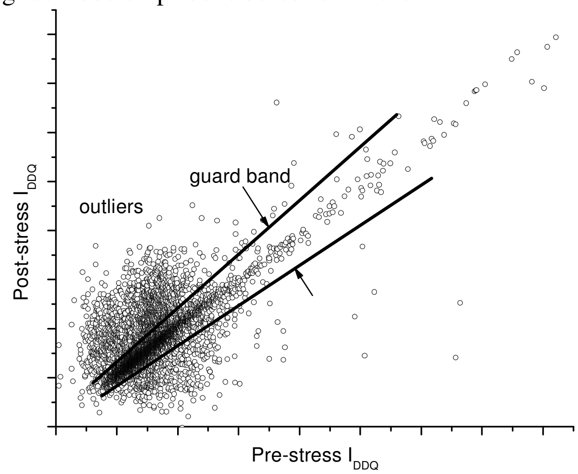

Figure 4. Scatterplot of Pre and Post-Stress I_{DDQ} Values.

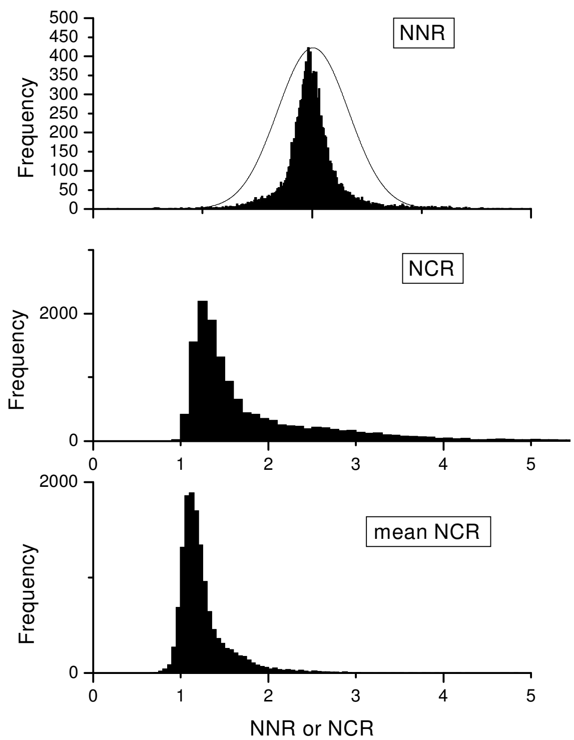

Figure 5. NNR, NCR and Mean NCR Distributions.

Since all chips considered for analysis pass all other tests (stuck-at, function, etc.), we need an oracle to define what we consider to be "defective" chips. In the presence of burn-in data, such oracle is readily available [4]. For TI data, post-stress I_{DDQ} measurements obtained under identical conditions as used for pre-stress I_{DDQ} measurement are available. We use these values for distinguishing between good and faulty chips. A deviation of more than 20% in any reading is considered to be indicative of a defect. The chips having post-stress I_{DDQ} measurement smaller than pre-stress I_{DDQ} measurement (healer chips) are also considered defective. This is conceptually illustrated in Figure 4 that shows the scatter plot of I_{DDQ} readings of all chips. The guard band (20%) shown is not to scale.

Table 2. Distribution parameters for NNR, NCR and Mean NCR for entire data set.

Metric	Mean (μ)	Std. Dev. (σ)	μ+3σ
NNR	-	16.27	-
NCR	2.03	2.51	9.56
MeanNCR	1.25	0.34	2.27

Table 3. Distribution of Chips for Different Metrics.

NCR↓	NNR				
	Accept	Accept	Reject	Reject	
Accept	10048	3454	39	-	Accept
Reject	10	56	-	-	Accept
Accept	59	50	75	30	Reject
Reject	15	12	13	9	Reject
	<20%	>20%	<20%	>20%	Mean NCR↑
	Post-stress I_{DDQ} Change				

Table 4. Distribution of Chips for Different Neighbor Groups.

Metric	A	B	C	D	Post-stress I_{DDQ} change
NNR Accept	2162	5445	2030	495	<20%
	496	1785	963	328	>20%
NNR Reject	10	63	43	11	<20%
	2	22	20	4	>20%
NCR Accept	2171	5498	2047	505	<20%
	492	1772	949	330	>20%
NCR Reject	1	10	26	1	<20%
	6	35	34	2	>20%
μNCR Accept	2165	5445	2005	486	<20%
	494	1772	937	325	>20%
μNCR Reject	7	63	68	20	<20%
	4	35	46	7	>20%

4. Results

TI Data for 17 wafers from 5 different lots and a total 13 879 chips is used. The average I_{DDQ} was obtained by averaging 10 I_{DDQ} readings for each chip. Figure 5 shows the distribution of NNR, NCR and mean NCR values. The thresholds for NNR, NCR and mean NCR are set at mean+3σ values shown in Table 2. The distribution of chips for these metrics is shown in Table 3. It indicates disparity between different metrics. Chips in each category are divided based on whether they are accepted or rejected by a metric. They are further subdivided depending on whether post-stress change in I_{DDQ} was less or more than 20%. NCR-based screening has the fewest false rejects and accepts. A tighter distribution of the mean NCR results in lower yield.

The success of a spatial correlation-based method depends on the availability of highly correlated dice used for parameter estimation. In order to see the effect of the number of chips used for estimation, we divided the data based on the number of neighboring dice used for prediction that came from different groups. The distribution of chips based on this criterion is shown in Tables 4. In Table 4, Group 'A' means that all 8 neighboring chips came from group 1 and group 2. Group 'B' indicates that dice from group 1, 2 and 3 were used for 8 neighboring positions, group 'C' indicates that dice from groups 1 to 4 were used and group 'D' means that dice from all five groups were used.

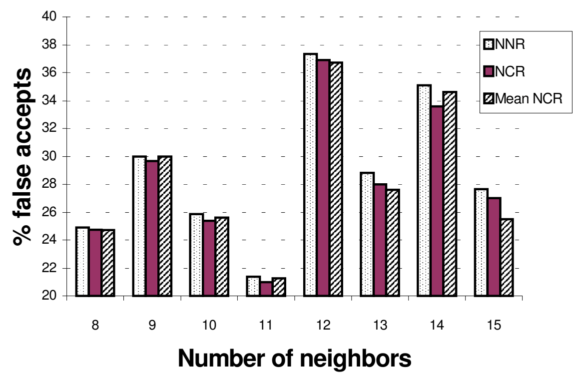

Figure 6. Number of false accepts for different methods.

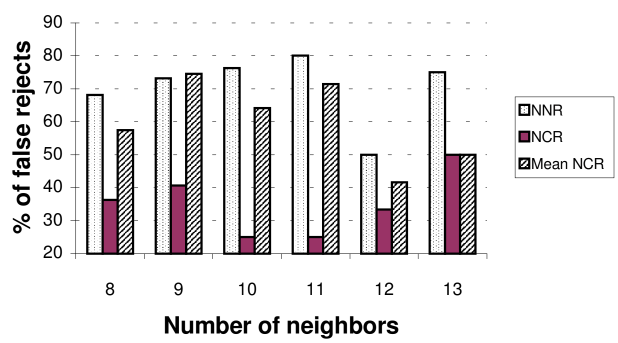

Figure 7. Number of false rejects for different methods.

Table 5. Defect Levels for Different Metrics.

Metric	A	B	C	D	All
NNR	18.66	24.68	32.17	39.85	26.1
NCR	18.47	24.37	31.67	39.52	26.3
μNCR	18.51	24.52	31.76	40.12	25.8

Figure 6 shows the number of false accepts for each method with varying number of neighbors. This value is computed as the percentage of defective chips out of all accepted chips (considering chips having more than 20% post-stress variation to be defective). It shows that all methods have similar defect levels. The defect levels increase as neighbors from longer distances are used for estimation. This could be because the dice at longer distances are not highly correlated to the reference die. When dice farther away are used, NCR screens defective chips slightly more effectively as it is uses *maximum* nonconformance to local neighborhood for screening chips.

Figure 7 shows the number of false accepts for each method with varying number of neighbors. This value is computed as the percentage of good chips that were rejected by a method. NCR accepts slightly fewer chips as long-distance neighbors are used. As correlation fades for dice from different groups, this can result in more yield loss.

Table 6. Yields for Different Metrics.

Metric	A	B	C	D	All
NNR	99.55	98.83	97.93	98.21	98.7
NCR	99.73	99.38	98.03	99.64	99.1
μNCR	99.51	98.59	96.10	96.65	98.0

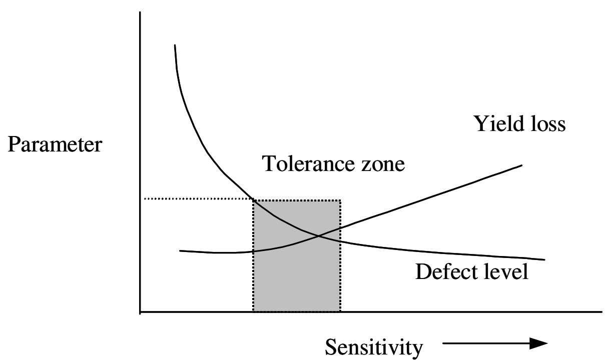

Figure 8. Metric Sensitivity and DL/YL Parameter.

In Figures 6 and 7 the group association of neighbors is not shown. In other words, 8 neighbors may come from different groups and need not be confined to group 'A' only. The disagreement among different metrics is relatively more for chips that are accepted and have less than 20% post-stress I_{DDQ} deviation. The metrics agree on "good" chips or chips that belong to the "core" population as estimated and actual values match for these chips. The disagreement occurs for outliers that are "hidden" in the core population as gross outliers alter properties of the distribution. A more sensitive metric like NCR can detect these chips. An alternate way to detect such outliers could be use of more resistant estimators [13]. Intuitively, NNR effectiveness can be improved if the median of median values is used [14].

The presence of outliers alters the tail of the distributions differently for different metrics as shown in Figure 5. The more relative a metric, the shorter the tail of the distribution. Thus, NNR results in a short-tailed distribution because it tends to average out the effect of gross outliers. On the other hand, these chips result in a long tail for the NCR metric. The mean NCR tends to have intermediate results.

5. Conclusions

Two schemes for wafer-level spatial estimation of fault-free I_{DDQ} were compared in this paper. Any relative parameter estimation scheme loses its accuracy when the estimator population is polluted by outliers. This situation is somewhat similar to Byzantine General's problem [15]. Should one use fewer "good" estimators or more "average" estimators when the knowledge of "good" or "average" is absent a priori? Clearly adding more chips from the spatial neighborhood is useful as long as they provide a reliable estimate of the parameter being considered. Therefore, using neighbors from longer distances is beneficial *only if* the chips in the neighborhood used for estimation are correlated to the reference die. Inaccurate estimation results in yield penalty. However, when a metric like NCR is used, considering neighbors at longer distances is useful for detecting some subtle outliers that cannot be detected by NNR due to averaging effect.

Whether one technique is preferred over other depends on the sensitivity requirements. A more sensitive methods can detect subtler outliers, probably at a higher cost of overkill. There exists a tolerance zone where both defect level (DL) and yield loss (YL) are acceptable as conceptually illustrated in Figure 8. In such case, either method is acceptable. Better quality goals can be achieved with NCR more easily than NNR.

Due to their inherent reliance on statistical properties of the distribution, threshold setting issue remains for all these methods. An optimum threshold may be decided through empirical analysis or prior engineering judgment. Increasing variance in I_{DDQ} values will limit the sensitivity of NCR/NNR methods. However, as long as the fundamental mechanisms that govern the variation are same, wafer-level spatial estimation will prove to be useful.

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