Clustering Based Identification of Faulty ICs Using I_{DDQ} Tests

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Abstract

Technological advances in design and process have led to questions being raised about the applicability of I_{ddq} testing. The main concern being the inability to differentiate between normal and faulty quiescent currents in ICs. In this paper, we propose a new methodology aimed at addressing this concern through the application of clustering techniques to identify ICs with abnormal I_{DDQ} values. Preliminary results of applying this technique in production test are also presented.

1. Introduction

The use of I_{DDQ} based test methodology to detect faults in CMOS ICs has been studied for several years [1,2,3]. Studies on leakage current based testing techniques [4,5] have concluded that it is necessary to include I_{DDQ} monitoring to obtain highly reliable CMOS ICs. Practical applications have shown that there is an increase in defect detection when I_{DDQ} monitoring is added to conventional tests [5]. Studies have also demonstrated that I_{DDQ} testing reduces line fallout after 99.6% stuck-at fault coverage failed to achieve desired quality goals [6].

There are several reasons for using I_{DDQ} monitoring for testing of ICs [7], [8]. Traditional IC testing techniques are not effective in detecting a number of failure modes in CMOS ICs. In general, faults such as gate oxide shorts, certain bridging faults, certain open faults, stuck-on faults, punch-through faults, operation induced faults, parasitic devices, p-n junction leakage, and abnormally high contact resistance, may not manifest as logic faults. Therefore, these kinds of defects will not be detected by traditional tests that monitor the output logic levels. In functional testing, the site of a fault has to be excited and the effect of the fault has to be propagated to the output. In I_{DDQ} testing, the propagation of the effect is automatic. In addition, it can provide transistor level resolution as opposed to gate level resolution.

Though the advantages of I_{DDQ} testing have been well documented, recently there have been concerns about the applicability of this test methodology in the future [9]. The main concern raised has been with the inability to differentiate normal I_{DDQ} current from abnormal I_{DDQ} current values as device geometries continue to shrink.

In this scenario, there have been some attempts to alleviate this problem by suggesting other methods of analyzing measured I_{DDQ} values. One good example of this is the current signatures approach [10]. The current signature technique identifies a faulty device by looking for a step in current values measured over a spectrum of applied vectors. However, since some designs might inherently have high current states, the proposed technique may mistake that as a failure mode and classify a device as being bad.

The approach proposed in this paper takes into account inherent high current states of the design in addition to being able to differentiate between good and bad devices even in the presence of large background currents. The proposed method does not rely on a fixed threshold, rather it detects devices with abnormal current distributions with respect to other devices in a batch.

The paper is organized as follows. An overview of clustering techniques and its application to I_{DDQ} testing have been discussed in section 2. This is followed by experimental results in section 3. Section 4 analyzes the experimental results in detail. Section 5 includes conclusions and future work.

2. Clustering

2.1 Background

Different Clustering techniques have been used in the past in varied disciplines including engineering, medical, biological and other areas to perform classification of large amounts of data. Here, an attempt is made to apply some of these same techniques to I_{DDQ} testing. Based on results from clustering and other inherent characteristics of the I_{DDQ} data set that is clustered, several hypotheses have been formed. Before going into details of the specific clustering techniques applied here, a brief history of clustering in various fields and their intrinsic characteristics may be useful.

Clustering techniques attempt to group points in multi-dimensional space in such a way that all points in a single group have a natural relation to other members in the group. Points that are not significantly different are grouped into different clusters. The idea behind applying clustering to a set of data points is to understand the data set better and to uncover whatever structure or pattern resides in the data. Clustering techniques are tools for discovery of these patterns rather than ends in themselves and help in forming statistical questions that form the basis for further studies. It should be kept in mind that the application and interpretation is subjective.

Several kinds of clustering algorithms are available and due to the subjective nature of the clustering problem, the task of finding the “best” technique is fruitless. Rather, the peculiarities and features of a clustering technique have to be considered while selecting the algorithm to be applied. A couple of important features that should be considered while choosing the algorithm include the user specifiable options for distance metrics, or measure of dissimilarity between two groups, computational cost, type of output, and the approach to treating outliers in the data set. Considering these criteria, the clustering program selected for our use is based on two common clustering techniques – the K-means algorithm and the leader algorithm. The program chosen is called Fastclus in the statistical analysis package SAS® [11].

Fastclus performs disjoint cluster analysis based on Euclidean distances and ensures that points within the data set are clustered such that each data point belongs to only one cluster. It employs the 'nearest centroid clustering' method. In this method a set of initial points called 'cluster seeds' are selected as a first guess of means of the clusters. Next, each data point is assigned to a cluster based on these initial cluster seeds to form temporary clusters. The initial seeds are then replaced by the means of the temporary clusters and data points are re-assigned to different clusters as necessary. This process is repeated until there are no further changes within clusters.

Due to the initialization method used, this algorithm is sensitive to outliers. As a result, often outliers appear as clusters with only one member. The number of initial seeds, and hence number of final clusters, minimum distance separating the seeds, along with other criterion on which the program groups the data set can be specified by the user.

2.2 Application to I_{DDQ}

Using Fastclus, clustering analysis was performed on I_{DDQ} measurements taken on a high volume device. The device used for our study contains a large number of gates (more than 100K) and has extensive Design-for-Testability (DFT) features incorporated. I_{DDQ} vectors used to obtain I_{DDQ} measurements on the test floor were generated using a commercially available ATPG tool.

For the purpose of our analyses, 30 different I_{DDQ} vectors were applied and measured on 630 devices from the same wafer lot. A fault coverage of approximately 95% (pseudo stuck-at fault model) was obtained for the 30 applied vectors. The data set presented here thus contained 30 I_{DDQ} readings for each device. Due to the proprietary nature of the data, all results have been normalized before presenting them. An upper limit was used to stop further measurements from being taken. If the I_{DDQ} reading of any device exceeded this upper limit, no further measurements were taken for that device.

While clustering the data set, to study the effects of specifying different number of final clusters, 2, 5, and 8 clusters were formed. This was done to analyze different scenarios and understand the effects of smaller number of clusters versus a larger number. The resulting clusters were groups of devices that exhibited similar characteristics for all 30 of the applied I_{DDQ} vectors. From these results, interpretations of faulty and fault-free devices can be made as explained in the following section.

3. Experimental Results

Figure 1 shows the results of specifying two clusters to be formed by grouping the 627 devices into either one of the two clusters. Cluster statistics of forming 5 clusters and 8 clusters are shown in figure 2 and figure 3 respectively.

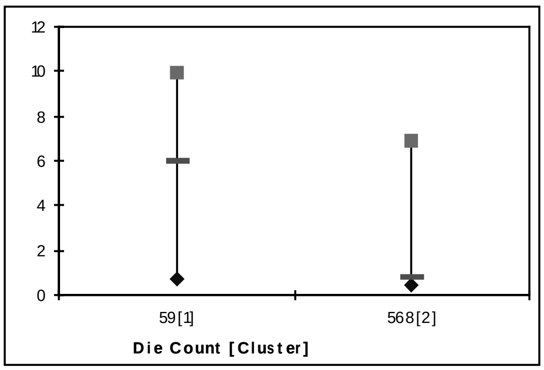

Figure 1: Cluster Statistics – 2 Clusters

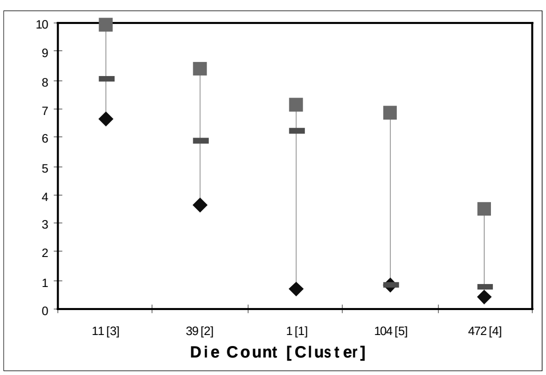

Figure 2: Cluster Statistics – 5 Clusters

By specifying three sets of clusters to be made (2, 5, and 8), good or bad device judgements can be made with varying degrees of confidence. Lower the number of clusters, lower the confidence in distinguishing between one cluster and the next. For this purpose, the same data set was used to perform analysis by re-running the algorithm to obtain different number of clusters. This analysis can give us the necessary data required to make judgments based on dynamic clusters instead of an absolute threshold value per vector.

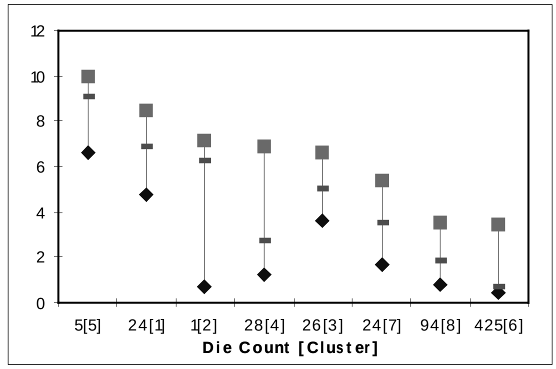

Figure 3: Cluster Statistics – 8 Clusters

The charts shown in figures 1, 2, and 3 represent the distribution of I_{DDQ} measurements across each device broken up by the cluster they belong to. The clusters and the total number of devices that belong to that cluster are shown on the X-axis. The I_{DDQ} measurements for all devices in that cluster are represented on the Y-axis. To elaborate, in figure 2, cluster 1 contains 1 device, cluster 2 contains 39 devices, cluster 3 contains 11 devices, cluster 4 contains 472 devices, and cluster 5 contains 104 devices. This accounts for all the 627 devices. In cluster 4, of the 472 devices assigned to it, the minimum I_{DDQ} measured was 0.4mA. The highest I_{DDQ} measured was 3.5 mA while the median for this cluster was 0.74 mA. From this analysis, all 472 devices in cluster 4 can be characterized as good devices. The devices in clusters 3, 2 and 1 can be classified as bad devices. Cluster 5 has 104 devices for which the min, max and median values are 0.87 mA, 0.87 mA and 6.86 mA respectively. Since the median for this cluster is very low, and yet based on the fact that they have been grouped into cluster 5 instead of cluster 4, there must be some defining characteristics that differentiate them from the devices in cluster 4. Hence, these devices cannot be labeled or classified as either good or bad devices. These are ideal candidates for further analysis. It should be noted that the high values of I_{DDQ} here are due to some of the high-current causing parts of the circuit not being completely turned off.

A normalized histogram of the I_{DDQ} when 5 clusters were formed is shown in figure 4. Cluster 4 which has only one device is not shown in this figure. From figure 4, it is clear that there is some overlap of I_{DDQ} between the different clusters. If there is a need to identify and target individual devices that have been observed to have a high I_{DDQ} value for further analysis or to perform diagnostics, it can be easily done from the data used to form this histogram.

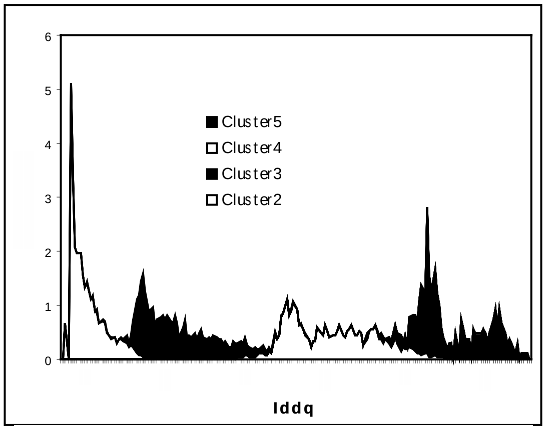

Figure 4: Normalized Histogram for the case with 5 Clusters

4. Discussion

With existing I_{DDQ} test techniques, threshold setting is generally determined apriori. In this methodology of using clustering statistics of I_{DDQ} data, the algorithm identifies groups of devices that are abnormal based on the I_{DDQ} values for all vectors that are applied to all devices. By using this algorithm to factor in low current states exhibited by fault-free devices as well as high current states due to inherent defect in the die, measurements of I_{DDQ} currents can be better utilized. If this methodology of clustering is applied to individual batches (lots) of devices, the clustering process will take care of batch to batch (or even lot to lot) variation in leakage currents. When this clustering algorithm is implemented on a typical batch of devices, a large cluster will be formed with all devices exhibiting low I_{DDQ} currents, potentially good devices. This will be followed by several clusters corresponding to abnormal I_{DDQ} readings (possibly with single or multiple high I_{DDQ}) that cannot be directly determined to be good or bad. Such a cluster can also contain a group of ICs with somewhat of an elevated current for a large number of vectors, each of which taken separately would not raise a flag.

A good use of this type of 'binning' devices based on I_{DDQ} measurements can be to target the same devices to different application end markets. In other words, targeting the same device to applications that have different power requirements. Telecom applications that require low power consumption ICs can utilize the devices in the large cluster which have low I_{DDQ} measurements across all vectors. The same device from one of the other clusters can be shipped to customers who are not overly concerned about their power consumption.

Another potential application of this approach is in production testing. Yield numbers cannot be sacrificed for savings obtained through reducing test time. Though comparing I_{DDQ} with a threshold can be done real time, it does not have the capability to differentiate between quiescent currents in a device that has high current states. Some circuits tend to have an inherent high current state that might be mistaken by previously developed techniques as a failure mode.

The enhanced clustering approach presented is a two step process. In the first step, a reasonably higher threshold (Th_{max}) which is well beyond the predetermined maximum current level (I_{max}) of the circuit can be used to weed out devices that are absolutely faulty. From experimental studies on a couple of devices, it was noted that a conservative estimate of Th_{max} can be arrived at by using the following equation:

$$Th_{max} = 5 * I_{max}$$

Whenever measured current for any particular vector is beyond this maximum (Th_{max}), further I_{DDQ} measurements on that particular die are ignored and the prober moves on to the next die. I_{DDQ} values measured on the above device are also excluded from the clustering analysis. The next step is the actual clustering process. The clustering approach has a delay in terms of determining faulty devices, however the benefits of accurate yield estimation and device binning far out weigh the delta increase in production test time.

5. Conclusion and Future Work

The process of separating a good device from a bad device based on I_{DDQ} has become tricky due to device integration, scaling of device geometries and reduction in threshold voltages

(V_T). Hence, it has become necessary to inspect measured I_{DDQ} currents in a relative perspective over a spread of devices rather than comparing with a static threshold value as done in practice. We have demonstrated that clustering of the measured I_{DDQ} will help accomplish this objective.

A process for making judgements based on I_{DDQ} measurements from the test floor was presented. An example of implementing the process on real devices was shown. Rather than using a single static I_{DDQ} threshold value, a new approach of using the I_{DDQ} measurements was put forth. While traditional practice is to treat each vector in isolation, the goal of our approach is to identify abnormalities in terms of measured currents for all I_{DDQ} vectors. In our opinion, such new techniques are what will have to be used for the continued use of I_{DDQ} testing in the industry. Using this technique, wafer-wafer and lot-lot or even fab-fab dependencies can be accounted for and utilized while accepting or rejecting devices.

Currently, we are working on comparing the presented technique to other approaches including signature analysis and presenting the results in a future forum. Further, we are currently performing failure analysis on a few of the devices that exhibited high I_{DDQ} currents (devices from cluster 5 in fig. 2), to determine the causes behind the high currents.

6. Acknowledgements

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7. References

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