Data Size Reduction for Clustering-Based Binning of ICs Using Principal Component Analysis (PCA)

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Abstract

Accurate binning of ICs using analog characteristics such as I_{DDQ} requires using data from a number of vectors. From this data, information needs to be extracted using a method that will yield sufficiently high resolution. Using a large volume of data can require significant computation time. If n analog measurements are made for each chip, the data has n dimensions. However the measured I_{DDQ} values for a chip can be highly correlated. We examine an approach based on Principal Component Analysis (PCA) for reducing the data size while preserving almost all of the information. PCA transforms the data by extracting statistically independent components and arranging them in the order of relative significance. Using industrial I_{DDQ} *data we found that often n-dimensional data can be reduced to a single dimension with no substantial change in the clusters identified.*

Keywords: Clustering-Based Binning, Principal Component Analysis, Single Dimensionality.

1. Introduction

The ICs coming off a production line can vary significantly in terms of performance and reliability related parameters, due to process variance and defects. They may need to be binned into several bins depending on suitability for an application environment and some rejected. I_{DDQ} has been a very useful parameter, and is considered to provide a unique combination of high fault coverage and small vector set [7]. I_{DDQ} not only impacts power consumption but also indicates reliability problems if it is abnormally high [1,8,17]. However shrinking of device geometries has made I_{DDQ} based testing increasingly difficult [15,23]. Even normal devices can have very high I_{DDQ}. It has also been shown that there is a correlation between maximum operating frequency f_{max} and I_{DDQ}, thus a high I_{DDQ} may represent a faster device [14] and not necessarily a low reliability device. That makes accurate binning an important economic consideration.

Achieving higher resolution in the presence of a large background current requires using multiple measurements and careful extraction of abnormal variation that may signal presence of a defect. Methods like current signature [5,6,16] and ΔI_{DDQ} testing [18,21] compare the quiescent current values to a set threshold limit or look for significant variation in quiescent current pattern of a device to identify it as defective. Another method recently proposed is the use of statistical clustering of the ICs based on their I_{DDQ} values [10,11]. Clustering is a powerful statistical method that has been successfully applied to different problems. However since clustering is an iterative process, it can require significant computation time when the number of devices involved is large. This problem can be significantly alleviated using a two-step approach [22]. The first phase involves separating an initial set of ICs into clusters using a suitable clustering algorithm. The second phase involves simply assigning the new devices to the closest possible cluster formed in the initial phase. The approach was optimized in [20] for maximum defect identification by determining the number of clusters that would give the best clustering solution.

In this paper, we examine an approach to further reduce the computation time needed. In this approach we reduce the dimensionality of the raw data using principal component analysis (PCA). PCA generates components such that the components are statistically independent and the first few components contain most of the information about the device. Applications of PCA in other fields have shown that the first few Principal Components (PCs) are able to provide a satisfactory clustering solution [3]. Various heuristics have been proposed to determine number of PCs to be used [9,12]. The selected components can be used to perform clustering. We find that the first principal component alone is enough to guide clustering, in which case, cluster assignment problem reduces to a simple one-dimensional thresholding operation.

The data reduction using PCA can significantly speed up the computations needed at the production line, however this may result in loss of some resolution. An objective of this study is to assess the potential impact of this loss.

In the next section, we provide a brief overview of principal component analysis technique. We then discuss the use of PCA for the two-phase binning approach. The results presented in section 4 compare the clusters obtained using PCA with those obtained using the complete data set.

2. Principal Component Analysis: A Brief Review

When many of the variables of a multi-dimensional dataset have a significant correlation, PCA successfully captures nearly all the information of the original dataset in the first few PCs. PCA mainly has three effects:

1. It transforms the data by defining new variables termed principal components, which are statistically uncorrelated. The new variables are linear combinations of the original variables.
2. It orders the resulting principal components in such a way that those possessing larger variance are arranged first.
3. In many problems, the first few components capture most of the discrimination capability. In such cases, only the first few components need to be considered.

PCA is applicable to data analysis problems in several domains where the data elements are significantly correlated. It is available as a standard technique in mathematical and statistical analysis packages. While a detailed discussion of the approach is beyond the scope of this paper, we briefly discuss the steps involved.

Let X be the (mxn) matrix of I_{DDQ} measurements, where m is the number of ICs and n is the number of I_{DDQ} measurements per device. Thus each row corresponds to one device and each column to one I_{DDQ} test vector. The I_{DDQ} data matrix X can be written as,

$$X = USV^T$$

where U is an (mxn) matrix, S an (nxn) diagonal matrix, and V^T is an (nxn) matrix. The above result from Matrix Theory is called Singular Value Decomposition (SVD), which is relevant to PCA in several respects. One way to carry out SVD and satisfy the equation given above is to first calculate V^T and S by diagonalizing X^TX:

$$X^TX = VS^2V^T$$

and then calculate U as follows :

$$U = XVS^{-1}$$

SVD provides a computationally efficient method of finding PCs. The matrices V and S will give us the eigenvectors and the square roots of the eigen values of X^TX. The diagonal values of matrix S makes up the singular value spectrum from which variances possessed by each PC is calculated. The height of any one singular value is indicative of its importance in explaining the data [12].

Matrix U yields scaled versions of PC scores. The PC scores or z-scores are also given in matrix form, Z=US=XV. Therefore, the scores given by U are simply those given by Z but scaled to have variance 1/(n-1). Z-scores are the coordinates of the I_{DDQ} values of a device in the space of principal components. The transformed variables are principal components and the individual transformed observations are termed the z-scores. We have used these scores as input to the clustering algorithms as opposed to I_{DDQ} values.

One can condition the data matrix X by centering each column and then X^TX is proportional to the covariance matrix of the columns (test vectors in this case). We can center each column of X before applying SVD by subtracting the column means of a matrix from the corresponding columns.

3. Implementation of PCA Based Clustering

The test data used here to evaluate the use of PCA for testing and binning of ICs was collected at Texas Instrument for a high volume 650K-gate device manufactured in deep sub-micron process [10]. The device has extensive DFT features including full scan. Thirty vectors yielding fault coverage of 95% were used for I_{DDQ} measurements on four lots containing 627, 724, 716 and 798 devices. The same dataset was used to obtain the results in [22]. We have used lot 1 for the cluster pre-forming (phase 1) and the remaining lots to evaluate the second phase of binning. Due to the proprietary nature of the data, it has been presented in a normalized form. PCA capability of MATLAB was used for performing our analysis.

3.1 Extraction of PCs

We compute principal components using the raw data (without standardization). This is generally appropriate when all variables are in the same units as in this case. Standardizing the data is needed when the variables are in different units or when variance among different columns is substantial. In case of commensurate variables, it was observed that standardization often reduces the quality of the clustering [19].

PCs / Lots	1st	2nd	3rd	4th	5th
Lot 1	98.79%	0.21%	0.19%	0.13%	0.11%
Lot 2	87.29%	2.63%	2.09%	1.58%	1.07%
Lot 3	85.4%	2.71%	2.12%	1.72%	1.48%
Lot 4	77.83%	7.99%	2.98%	2.08%	1.69%

Table 1. Variance possessed by the first five PCs for lots 1, 2, 3, and 4.

With many types of data sets, it is common for the first few principal components to possess most of the variance of the original data. We have applied PCA to lots 1, 2, 3 and 4 individually. Table 1 shows the variance associated with the first five PCs. We notice that the first PC itself covers over 98% of variance in lot 1. When using PCA to approximate a data matrix, the fraction of the total variance in the leading PCs is used as a criterion for choosing the number of PCs for further analysis. Heuristics for selecting the significant components and for discarding variables that have a large component in low variance directions have been proposed [9,12]. One approach is to pick PCs such that the cumulative relative variance becomes larger than a certain pre-specified threshold. The best value for this cutoff will generally become smaller as n, the number of original variables increases. The first PC possesses at least 75% or more variance for all the four lots of our dataset. Thus, the number of PCs required to cover almost the entire variability of the dataset would be very small, reducing the dimensionality significantly.

Analysis with various numbers of PCs used reveals that the two-phase binning process is carried out successfully with a single PC and with negligible loss in resolution as compared to case where more PCs are used. The z-scores are calculated for all the devices in lot 1 from the PCs considered being significant and they are then fed to the clustering algorithms. The z-score of a device is thus represented by

$$Z_{ix} = \sum X_{ij}.V_{jx}$$

where, index i denotes the device number, and x (= 1) the number of principal components used. Variable j corresponds to the number of test vectors in the dataset (j=1,…30). Matrix X is our original IDDQ dataset and matrix V is a column matrix since we consider only one PC as significant. Thus, Z_{ix} is also a column matrix and is a linear combination of all the IDDQ values of a device. The coefficients in matrix V are based on the data matrix and are not arbitrary.

3.2. The Two-phase Binning Approach Using PCA

This technique, which has two phases, is described in [22]. The first phase identifies the clusters and the second phase does the real-time binning. In our analysis, we have used the first lot for cluster pre-forming (phase 1) and lots 2, 3, 4 to evaluate the binning process. This paper only addresses utilizing PCA to go about this approach and get a satisfactory clustering solution. The paper also gives an insight to the advantages of using PCA in this analysis and suggests an optimum approach for going about this method.

Clustering Phase: In this phase, the data is pre-processed using PCA as explained earlier before feeding it to the clustering algorithm. After this, a rigorous analysis is carried out to determine the best clustering of the devices. These clusters can then be characterized as defective, non-defective, low power, high-speed, etc. These preformed clusters would be based on an initial lot of devices produced or a set of samples. It is also possible to modify these clusters by conditioning them further based on their analog and digital characteristics. During this phase, we have to take note of certain specific values (like the column means) that would be further useful while binning of every device and condition the device properties. It is important to condition the device characteristics in exactly the same manner during both the phases so that bin characteristics found for initial devices can be used in the binning phase. In this study we have used the z-scores as the input to the clustering algorithm.

Binning Phase: In binning phase, as each IC comes off the production line the measured I_{DDQ} values associated with it have to be conditioned the same way as during clustering. The dimensionality of the z-score used here will depend on the number of PCs considered to be significant for clustering in the first phase. In this paper we use a single dimensional z-score value for every device in this phase because we consider only the first PC significant for our analysis.

Binning phase requires comparing the z-score of the device with the centroids of different clusters. A device is assigned to the cluster that represents the closest match. Since this implementation uses just one column of z-scores it is much faster than the conventional method and thus the process efficiency is significantly increased with much reduced computing. The binning steps for Hierarchical and K-means algorithms are the same once the dataset is preprocessed [22]. The only difference here is that we feed z-scores to the clustering algorithms and not the actual I_{DDQ} values from the dataset as in [22].

4. Evaluation of Results of PCA Based Clustering

We use the *silhouette plots* to determine the quality of the clusters formed. The silhouette value for each device is a good indication of how similar the device is to the other devices in the same cluster as compared to the devices in other clusters. It is computed using

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}},$$

where, a(i) is the average distance from the ith point to all the other points in its cluster, and b(i) is the average distance from the ith point to all the points in the nearest neighbor cluster. The value of s(i) is between –1 and 1. The closer the value is to unity, better is the classification of the device.

We can define a quality index for the clustering of the devices by the overall average silhouette plot, defined as the average of $s(i)$ over all the objects i in the dataset. In general, we select the number of clusters, which yields the highest average silhouette width, which we call the *silhouette coefficient.* If the silhouette coefficient (SC) is higher than 0.71, the partitioning structure is regarded to be strong [13]. However if SC is less than 0.50, the partitioning structure is regarded to be weak or artificial. In this study we have used MATLAB as the computational tool.

4.1 Hierarchical Clustering-based Binning Using PCA

Figure 1 shows that using a single column of z-score accomplished a very stable clustering solution, similar to that given in [22] which uses all the thirty I_{DDQ} values of every device. The initial clustering is carried out with the first lot containing 627 devices. Given enough information about design parameters, observations based on parameters of interest can be associated with these clusters.

In analyzing figure 1, we see that there is only one weak member in cluster 4, and rest of the weak members belong to cluster 5. There are 35 weak members as compared to 31 by the previous method in which all thirty I_{DDQ} values were used compared to only one PC used here. Note that the silhouette values have been calculated using the entire set of I_{DDQ} vectors. Thus the results of first phase are nearly as good as those from previous method [22] even though we have carried out the first phase with only one column of z-scores, which has reduced the computing time drastically.

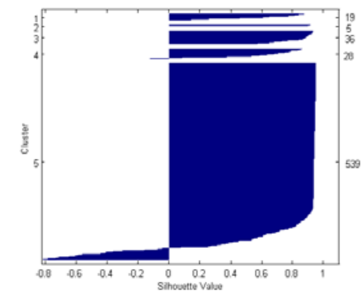

Figure 1. Silhouette plot for clusters obtained from lot 1 using Hierarchical clustering.

In comparing the individual devices we find out that only 19 devices are such that they belong to different clusters in the two methods. The 35 weak members are of special interest to the test engineer who may want to examine them further. For figure 1, the silhouette coefficient of 0.79 suggests that a strong clustering structure has been found. In figure 2 one interesting observation is that all the weak members belong to cluster 5. There was a weak member with very low negative silhouette value in cluster 4 as seen in figure 1. But after binning, the characteristics of cluster 4 are modified such that the weak device no longer shows a negative silhouette value, indicating that it is grouped appropriately. In the previous method, there are 3 groups showing weak devices as compared to only 1 group showing weak devices here.

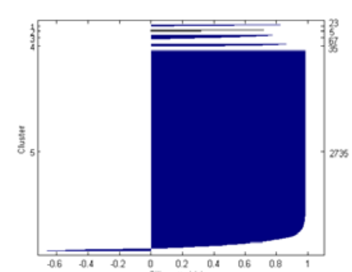

Figure 2. Silhouette plot after binning lots 2, 3, 4 using Hierarchical clustering.

The number of weak members in the binning phase is 5, which is slightly higher compared to that with previous method. But this technique offers much faster speed and better overall cluster

Method	Phases	# of devices	CLUSTER					# of weak members	Uncertainty (%)	Time (sec)
			1	2	3	4	5			
Hierarchical Method	Pre-forming Lot 1	627	529	37	46	14	1	31	4.90	26
			539	***28***	***36***	***19***	***5***	***35***	***5.58***	***6.54***
	Binning Lots 2, 3, 4	2238	2193	7	35	3	0	1	0.04	4
			2196	***7***	***31***	***4***	***0***	***5***	***0.22***	***1.16***
K-means Method	Pre-forming Lot 1	627	390	123	32	20	62	23	3.60	0.69
			391	***123***	***32***	***20***	***61***	***23***	***3.60***	***0.32***
	Binning Lots 2, 3, 4	2238	2133	68	8	4	25	22	0.98	4
			2133	***69***	***8***	***3***	***25***	***19***	***0.84***	***1.16***

Table 2. Enhancement due to clustering-based binning using PCA.

characteristics as we have seen from figure 2. The silhouette coefficient increases significantly to 0.92 after the second phase, which means that the grouping is very stable. After the second phase 2196 devices are assigned to cluster 5, and 42 devices are assigned to other clusters.

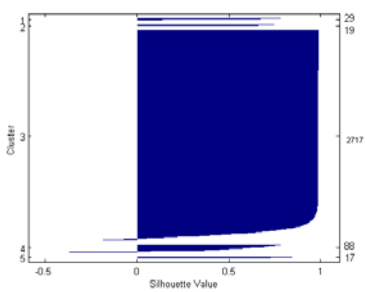

Figure 3. Silhouette plot for clusters obtained from clustering all the lots together using Hierarchical clustering.

Figure 3 gives the silhouette plot if all the lots are clustered together using Hierarchical clustering method using only 1 column of z-scores. It turns out that devices are grouped in 5 clusters, each cluster showing non-zero number of devices in them. The previous method could only form 3 clusters with at least one device when all the lots were clustered at once. An examination of Figure 3 gives us an insight as to how well this two-phase approach approximates clustering of all the devices together. For Hierarchical clustering algorithm, only 61 out of 2865 devices were grouped differently in the two approaches giving us a discrepancy factor of 2.21%. This suggests that this two-phase approach yields results very similar to the case if all the devices are clustered together.
The total weak members when all lots are clustered at once is 47 which is comparable to a total of 40 weak are members obtained by the two-phase binning, again indicating that it gives nearly the same results as if all the lots were clustered.

4.2 K-means Clustering-based Binning Using PCA

The procedure was repeated for K-means clustering. When all the devices in each cluster formed by the PCA approach were compared with the devices in the appropriate clusters formed using all thirty I_{DDQ} measurements, it was found that only one device was assigned to different clusters by the two methods. Thus the characterization of the clusters in [22] applies to the results obtained here for K-means algorithm. The number of weak members for the first phase is same in both the methods. A silhouette coefficient of 0.8 for phase 1 indicates that a good initial set of clusters is established. Lots 2, 3, 4 were binned using one column of z-scores, and we found that only two clusters showed weak members.

The results are the same as in [22] with the only difference being in 2 devices that were assigned to different clusters. The total number of weak members is 42. A silhouette coefficient of 0.96 indicated that the devices have been grouped extremely well for K-means algorithm. The computation time for this approach is much less than for using the entire set of I_{DDQ} values for clustering. The results based on PCA are also found to be the same as that based on all I_{DDQ} vectors given in [22], when all four lots are clustered together. For K-means, 82 devices were grouped differently with a discrepancy factor of 2.86%.

4.3 Discussion

The results for the proposed and the prior method are summarized in Table 2. The italicized and underlined numbers represent the results obtained using PCA. Table 2 gives the number of devices in each cluster along with the number of weak members. The uncertainty factor [22] is the fraction of weak members in the lot. For lot 1, in phase 1 this approach results in 35 weak members with Hierarchical clustering, compared to 31 with the previous approach. PCA based method produces 5 weak members in phase 2, as compared to the previous method. We observe that the uncertainty factor for Hierarchical clustering is slightly higher in both the phases using PCA, but for the K-means the uncertainly factors are almost the same for both phases. We have studied the results of applying different number of significant PCs to both the clustering algorithms. In the table 3, we compare the results using PCs to that obtained in [22]. Analysis shows that adding any further PCs after the first one do not result in any significant advantage [2].

Table 3. Particulars for lot 1 using up to 5 PCs

No of PCs	SC	W_m	C_1	C_2	C_3	C_4	C_5
1	0.789	36	539	28	36	19	5
2	0.8	27	530	28	45	19	5
3	0.799	30	530	37	45	14	1
4	0.818	19	455	37	120	14	1
5	0.787	37	538	37	37	14	1
Entire dataset	*0.79*	*31*	*529*	*37*	*46*	*14*	*1*

The results indicate that removing features with low variance acts like a filter, which provides a more stable and robust clustering. This is also observed in [3]. Using just a single PC does not result in a significant loss of resolution. A significant advantage of converting the problem to single dimension is that the clustering solution is easily visualized and can be adjusted using expert judgment.

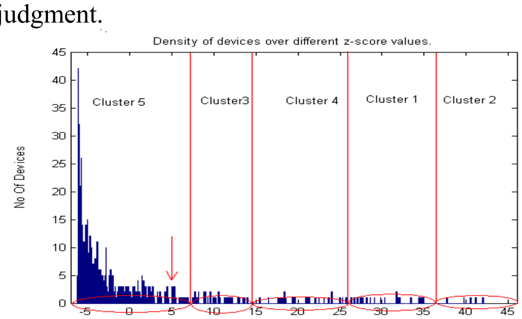

Figure 4. Density of devices over different z-score values also showing clusters using Hierarchical clustering.

Figure 4 shows the clusters formed when the first column of z-score values is fed to the Hierarchical clustering algorithm and the number of devices having a particular z-score.

After the first phase, the test engineer can study the characteristics of the weak members and simply adjust the centroid values of the clusters on the x-axis so that all the weak members are binned accurately after that. From figure 3 we know that 35 weak members belong to cluster 5 so we easily envision that the devices, which lie on the left side of the dividing line separating clusters 5 and 3, in figure 4 are the weak members. They are shown with an arrow in figure 4. Figure 4 gives the width of every cluster, which can be used for future reference. This assignment has been highlighted using the oval shaped structures on the x-axis. Note that from computation point of view, the binning phase of the clustering and I_{DDQ} test problems have been reduced to a simple thresholding problem with this method. However, the first phase (clustering) provides a set of threshold values based on initial lot overcoming the need for setting thresholds in an arbitrary manner.

Another parameter of interest is the computation time needed for the two methods. As expected this method is much faster for both the phases. Since the first phase is offline its computation time may not be a significant consideration. But the binning process, which is implemented on the production line, is of particular interest to us. It is seen that using this approach, it takes only 29% of time as compared to the previous method.. The computation time was measured on UltraSPARC processor with clock speed of 400 MHz as in [22].

The ease of visualizing and strong control over clustering is only possible because the problem has been converted to single dimension. Also, the first phase (clustering) provides a set of threshold values based on initial lot overcoming the need for setting the thresholds in an arbitrary manner.

5. Conclusion

With increasing difficulty in separating good and bad devices due to device integration, scaling in device geometries, and increased quiescent current levels, it has become important to inspect the IDDQ current distribution over a set of devices rather than comparing with a static threshold value. PCA is used to simplify the IDDQ testing and binning process by capturing the information in multiple IDDQ test vectors (30 in this case) to a smaller set of z-scores (one in this case) thus making the process easy to control and computationally efficient. In case of clustering, it is seen that using very few z-score values for a device instead of all the test vectors, provides us with negligible loss in resolution with much lower computation time.

Results using industrial test data show that with just the leading principal component a good stable clustering solution can be found without any significant compromise on quality of clusters, compared to prior approaches that use the complete raw data set. This approach offers a potential practical technique of addressing the problem of binning and testing of ICs with a large number of test and measurement values. Reducing the data to a single dimension also facilitates easy visualization and permits use of expert judgment.

The proposed technique is also applicable when the data includes other analog measurements beyond just I_{DDQ} values. There exist other PCA based approaches for data discrimination. Some of them employ the last few principal components. Further research is needed to evaluate the applicability of such methods for binning of IC chips using analog attributes.

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