

Characterizing Cell-to-Cell Coupling in Flash Memory

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Abstract

Cell-to-cell coupling is characterized based on input/output data obtained from state-of-the art commercial multi-level cell (MLC) flash memory chips. The method is based on carefully choosing a mask that contains a number of local cells and then taking sample means conditioned on specific local input patterns for the cells captured under the scanning mask. These conditional means provide valuable information based on which coupling between a pair of cells is characterized.

Keywords: cell-to-cell coupling, flash memory, interference

1. Introduction

As cell density increases and aggressive dimensional scaling continues in flash memory design, cell-to-cell interaction via voltage-gate capacitive coupling is becoming a serious impediment in reliable recovery of data [1]-[3]. Cell coupling gives rise to interference that can seriously affect the means and variances of the read values for nearby cells [4][5]. In this work, we focus on quantifying the coupling factor between an arbitrarily chosen pair of MLCs. Specifically, we devise a method that makes use of available input and output data for a block of MLCs to extract the coupling factor for a particular pair of cells. The challenge is to isolate the effect of deterministic interaction between two particular cells amid the effects of other potentially coupled cells as well as random noise and the random portion of collective interference.

2. Mask and Conditional Means

Let P represent the mask or, equivalently, the cells contained in the mask. In this work, the mask is chosen so that it contains the victim cell V , a potentially coupled cell A whose impact on the victim cell is under

investigation, and a number of distant cells D whose impact on the victim can be safely ignored but are necessary to provide statistically meaningful sample size for the population of the conditional means. Fig. 1 shows an example mask.

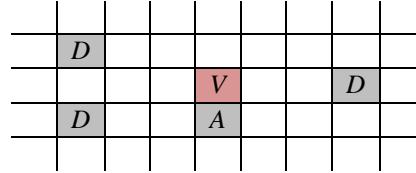


Figure 1: Mask P containing 5 cells (columns and rows represent bit lines and word lines, respectively)

Let p represent the specific input values for cells in P . Then, P can be viewed as a random variable (RV) with p taken as a specific realization of P . Ignoring the interference coming from D , the read value for the victim cell corresponding to a particular local input pattern (for all cells in the mask) is now written as a p -dependent function:

$$r(p) = x(v) + n(p) + f(v, a) + f(P^c) \quad (1)$$

where $x(v)$ is the input value for the victim cell, $n(p)$ is the zero-mean random noise that depends on p , $f(v, a)$ is the (v, a) -specific interference that is deterministic given a p , and $f(P^c)$ denotes the interference due to cells outside the mask P . The samples of $r(p)$ can be collected as the mask scans the 2-dimensional read data while looking for the specific local pattern p . We remark that $f(P^c)$ is a RV since P^c is random (i.e., the cell input values in P^c are not fixed). All lower-case letters denote specific realizations of the corresponding RVs (e.g., a denotes a particular input value of the affecting cell).

Taking the p -specific sample mean, we get

$$\bar{r}(p) = x(v) + f(v, a) + \bar{f}(P^c) \quad (2)$$

where the overbar denotes average. For the next step, consider taking a subset of these p -specific means so

that each subset corresponds to a common v value; the RV representation of this subset can be written as

$$r(v, A) = x(v) + f(v, A) + \bar{f}(P^C). \quad (3)$$

Note that A is now a RV, as the corresponding cell is no longer associated with a specific input value. The mean of the RV $r(v, A)$ is

$$\bar{r}(v, A) = x(v) + \bar{f}(v, A) + \bar{f}(P^C) \quad (4)$$

and thus the variance of $r(A)$ can be written as

$$\sigma_{r(v, A)}^2 = E\left[\left[f(v, A) - \bar{f}(v, A)\right]^2\right] \triangleq \sigma_{f(v, A)}^2. \quad (5)$$

Let S_A denote the threshold-voltage shift of cell A in the last step of MLC writing. Fig. 2 illustrates the two-step writing process of an MLC, where the first and second bits come from two different logical pages and are written at two different times. The S_A values can be seen as $\{0, \text{PV2-PV2}', \text{PV3-PV2}', \text{PV1-ER}\}$. Let us assume that the amount of threshold-voltage in the victim cell due to the coupling effect is linearly related to S_A [3], i.e., $f(v, A) = c(A, v)S_A$, where $c(A, v)$ is the coupling factor between cell A and the victim cell with input v . The variance of $f(v, A)$ is then

$$\sigma_{f(v, A)}^2 = c^2(A, v)\sigma_{S_A}^2 \quad (6)$$

where $\sigma_{S_A}^2 = E\{[S_A - \bar{S}_A]^2\}$. Each level in S_A occurs with probability 1/4 and $\sigma_{S_A}^2$ can be obtained easily.

From (5) and (6), we get $c(A, v) = \sigma_{r(A, D)} / \sigma_{S_A}$.

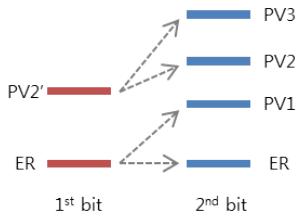


Figure 2: Two-stage writing of an MLC.

3. Experimental Results

Table I shows $c(A, v)$ values extracted, as A changes from one neighboring cell to another. It turns out that $c(A, v)$ is not a particularly sensitive function of v so results are shown only for $v = \text{PV1}$. Two cases are shown separately: 1) the victim cells are on odd-bit lines and 2) they are on even-bit lines. The center cells represent the victim cell and the values that fill individual cell positions represent the corresponding coupling factors. Because the programming sequence is such that for a given word line (row) programming

for odd-bit line cells are completed after programming for even-bit line cells are, program disturbance characteristics are different for two cases. Also, for our data, for a given bit line upper (upper row or word line) cells are completely programmed before lower cells are done. Based on experimentally observed results, we have $\sigma_{S_A}^2 = 1.75$ for the affecting cells on odd-bit lines and 1.65 for those on even-bit lines. It can be seen that for the victim cells on odd-bit lines, the lower cell dominates in terms of the coupling effect. The top three cells have negligible effect; this makes sense since the top cells are programmed before the victim cell. The side cells (which are on even-bit lines) also have little effect as they are completely programmed before the victim cell is. Note that the coupling effect is typically in the form of a lift in the threshold voltage level of the already programmed victim cell due to the voltage level change that occurs later in a coupled cell [3]. For the victim cells on even-bit lines, the lower cell again is dominating but the coupling effect for the side cells cannot be ignored. This is expected as the side cells are now on odd-bit lines, for which the second bit programming is done after the programming is completed for the victim cell.

Table I: $c(A, v)$ for different interfering cells.

0.00	0.00	0.00	0.01	0.00	0.01
0.01	PV1	0.01	0.05	PV1	0.06
0.02	0.11	0.02	0.03	0.11	0.04

victim on odd-bit line

victim on even-bit line

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References

- [1] J. Lee, S. Hur and J. Choi, "Effects of floating-gate interference on NAND flash memory cell operation", *IEEE Electron Device Letters*, vol. 23, pp. 264-266, May 2003.
- [2] K. Kim, "Future memory technology: Challenges and opportunities", in *Proc. Int. Symp. VLSI Technol.*, pp. 5-9, Apr. 2008.
- [3] G. Dong, S. Li and T. Zhang, "Using Data Postcompensation and Predistortion to Tolerate Cell-to-Cell Interference in MLC NAND Flash Memory", *IEEE Trans. Circuits and Systems I*, vol. 57, no. 10, Oct. 2010.
- [4] J. Moon, J. No, S. Lee, S. Kim and J. Yang, "Statistical Analysis of Flash Memory Read Data", *IEEE GLOBECOM*, Dec. 2011.
- [5] J. Moon, J. No, S. Lee, S. Kim, J. Yang and S. Chang, "Noise and Interference Characterization for MLC Flash Memories", *IEEE ICNC*, Jan. 2012.