Statistical Optimal Design of Microelectromechanical System (MEMS)

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ABSTRACT

A three-step technique for MEMS quality optimization is demonstrated. It exploits the relative merits of its constituent optimization components. Analog Devices' ADXL50 accelerometer was the test device with microstructure dimensions serving as design parameters. Manufacturing design rules [7] and sensor performance requirements served as design constraints. A static model relating input acceleration to sensed voltage was used, neglecting sensor and signal conditioning dynamics. The trimming yield of the ADXL50, with sensitivity as the design target, was improved by 37%. We show that the three-step method enables the search for an optimal design in a semi-automatic manner by facilitating user interaction. Our final goal is to enable the generation of MEMS mask layout while ensuring robust designs with minimum sensitivity to fabrication process variations.

$Keywords$: Microelectromechanical system(MEMS), statistical MEMS design, yield optimization, MEMS reliability, robust design, Taguchi Method

1 INTRODUCTION

With MEMS feature sizes approaching micron and submicron levels, the MEMS performance matrix is rendered more sensitive to variations in design parameters and ambience. Manufacturing yield is concerned with deviations in device performance due to parameter variations induced by fluctuations in the manufacturing process. Operational reliability concerns the effects on MEMS device performance due to component degradation. Bearing this in mind, an optimal and robust design, is highly desirable with regard to device operation and fabrication. The goals of quality optimization are twofold: (1) Attenuate excessive scatter or variance around a mean. (2) Reduce deviation of the mean itself from a desired target value.

We first review some important quality optimization techniques that have evolved over decades of research in IC design. Section 2 includes a summary of algorithm performance in terms of convergence, scalability with dimension and applicability. In Sec. 3 we introduce the three-step quality optimization method with application to the ADXL50.

2 COMPARISON OF QUALITY OPTIMIZATION TECHNIQUES

In this section, we compare five quality optimization techniques: The Simplicial Method (SAM), The Center of Gravity Method (CGM), The Worst Case Distance Method (WCD), The Taguchi method, and The Statistical Performance Variability Reduction (SPVR) method. Critical performance characteristics for each method are evaluated by implementing their representative algorithms. The strengths and limiting features of each algorithm are studied. The following nine metrics are used to characterize the performance for the studied yield optimization methods.

1. Convergence
2. Computation
3. Dimensionality vs Cost
4. Accuracy
5. Designer interactability
6. Initial design initial guess
7. Space device parameter (D space) or process disturbance (P space)
8. Objective function
9. Assumptions

Table 1 summarizes our study of the five techniques. Comparisons are qualitative with details provided in [6].

3 METHOD

Based on Table 1, a new quality optimization method is introduced. A three-step method seeks to achieves the dual goals of variability reduction and target performance attainment.

1. Geometric yield optimization (GYO) as implemented by the WCD method, is first employed to bring the design close to the target. This is based on the following considerations:

- GYO places no requirements on the initial design. In other words, the starting point may or may not lie in the feasible region thereby eliminating the dependence of the optimal solution on the starting point by using grid-based initial designs.

- Compared to statistical methods including statistical yield optimization and SPVR, it exhibits good convergence. The WCD algorithm [1] often converges in less

Characteristics	SAM	CGM	WCD	SPVR	Taguchi
Convergence	steady,slow	unsteady,fast	steady,fast	unsteady,fast	none
Computation cost	large	large	small	large	small
Dimensionality vs cost	expotential	constant	linear	constant	linear
Accuracy	high	high,unsteady	low	high,unsteady	high
Interactability	No	No	No	No	Yes
Initial design	Yes	Yes	No	Yes	No
Space	D	D	D.P	D.P	D.P
Assumption	Feasible region convex	None	None	None	Small design space

Table 1: Performance Characteristics Comparison

than 10 iterations. Thus, reduced computational cost is another attractive feature.

2. The design is tuned using an appropriate desirability function [3] to reduce performance variability. This is based on the following considerations:

- methods aimed at reducing performance variability take the performance distribution into considerations. The desirability function which is sensitive to performance distribution tends to tighten the quality criteria.
- the quality loss function as evaluated by WCD in the GYO step is ill-behaved. At designs close to the optimal point, it does not accurately represent degeneration or improvement of quality.

3. The Taguchi method; the optimization process of Step 2 must often be terminated manually. Also, manual tuning of the resultant design might be necessary. The Taguchi method facilitates adjustment of the design parameters without harming the quality. It also affords the possibility of further improvement in quality. Our method is illustrated in Fig. 1.

The ADXL150's proof-mass-flexural-element was used as a test problem. The ratio of input acceleration to output voltage, termed the accelerometer sensitivity, is the performance metric. Typically, laser trimming of resistors ensures compliance with tolerance limits. However, if the sensitivity is severely out of range the part must be rejected since trimming is no longer effective. Thus, reduction of the statistical scatter and target tuning of the accelerometer sensitivity mean constitute the focus of the three-step method. The processing electronics were not included in the design and will be addressed in future efforts. We used a static as opposed to dynamic model to relate the proof-mass displacement in terms of the applied acceleration. The sensitivity of this capacitive accelerometer corresponds to the static position of the proof-mass. Hence sensitivity is determined by (1) The displacement of the proof mass due to applied acceleration and (2) The gain of the differential capacitor [5]. The sensitivity has been derived as [5],

$$\frac{V_o}{a} = \frac{2C_0}{2C_0 + C_{para}} \frac{m}{kg_0} V_m \qquad (1)$$

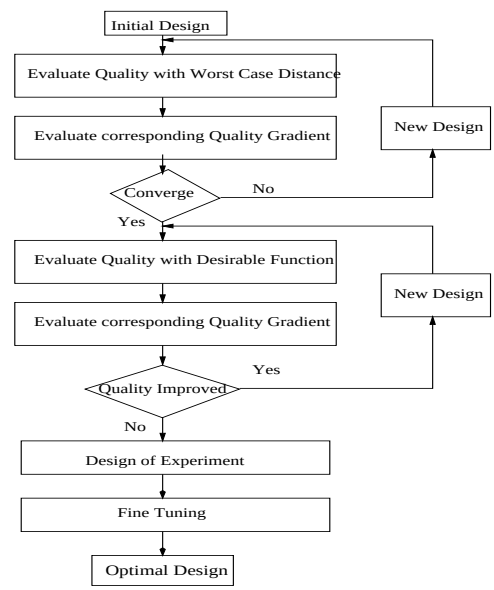

Figure 1: Flow Chart Detailing the Quality Optimization Flow

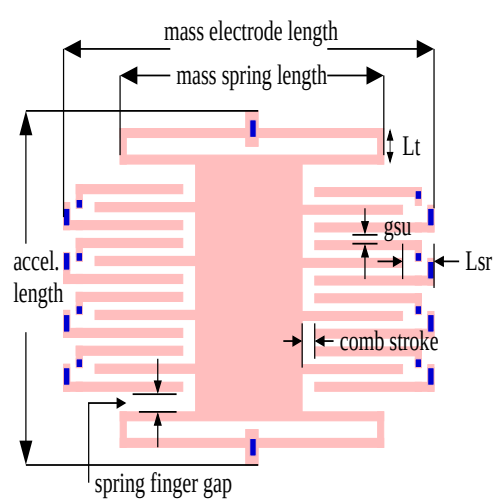

Figure 2: Proof Mass Structure with Appropriate Design Parameters

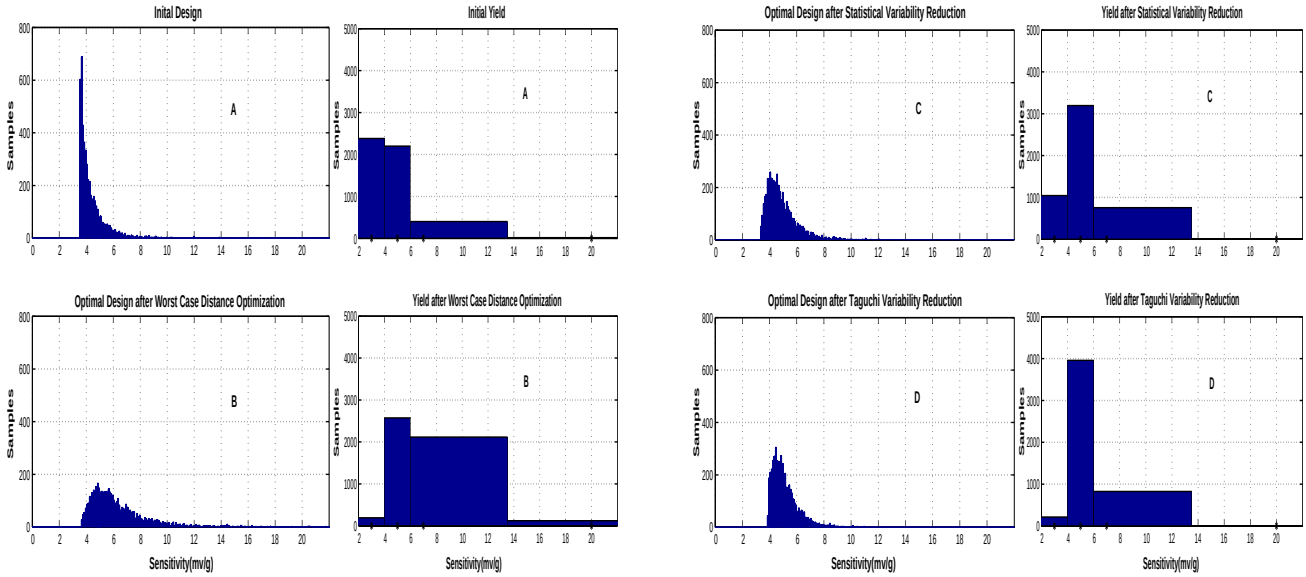

Figure 3: Histogram of Accelerometer Sensitivity Distribution Before and After Each Step of Quality Optimization (sensitivity target=5mv/g)

where, C_0 is the static electrode overlap capacitance, C_{para} the parasitic capacitance between moving electrodes and substrate, V_0 the sensed voltage, a the acceleration, m the proof-mass, V_m the bias voltage, k the effective spring constant, and g_0 is the initial air gap between electrodes.

The process space is sampled by assuming a uniform etching model [8]. So, a normal distribution for the etch rate is assumed and the same discrepancy is applied to *each* accelerometer dimension. The population of devices thus created is used for study. Figure 3 B plots the sensitivity distribution of the design obtained from the WCD approach in Step 1. The nominal design has been tuned from $3.6mv/g$ to $4.4mv/g$. Assuming the trimming process can handle sensitivity variations from $4mv/g$ to $6mv/g$, the yield will improve from 42.76% to 50.48% estimated by 5000 samples. Although the improved design ($4.4mv/g$) represents a significant improvement over $3.6mv/g$ with respect to a $5mv/g$ target, improvement on trimming yield is still insufficient. This is attributed to an increase in sensitivity fluctuation. The sensitivity standard deviation has worsened from $1.3mv/g$ to $2.6mv/g$. The sensitivity distribution is asymmetric with a mean at $6.5mv/g$ which is still off-target.

Figure 3 C is a plot of the sensitivity distribution of the optimized design via SPVR in Step 2 of our proposed method. The initial design for Step 2 is the result of the design process in Step 1. Through variability reduction, the sensitivity standard deviation has decreased to $1.3mv/g$. Accordingly, the trimming yield has improved from 50.68% to 63.92%. However, the sensitivity for the optimized design is only $3.9mv/g$. While it may appear to be inferior to the initial design with a sensitivity of $4.4mv/g$, this design corresponds to a far superior trimming yield. This can be deduced from the sensitivity distribution in Fig. 3. The final design has a mean of $4.9mv/g$ as compared to $6.5mv/g$ for the initial design. The improvement in quality indicates that performance variability and not yield is a better optimization criterion for on-target design. This is because performance variability takes the performance distribution explicitly into account.

Figure 4 plots the SNR (a measure of statistical variance) and statistical mean with respect to different device design parameters in a factor level experiment. Spring beam width and the air gap have the greatest effect on the sensitivity variability. The spring beam length and electrode overlap also significantly affect the SNR. The best values for these parameters are $5\mu m$, $10\mu m$, $268\mu m$, and $110\mu m$ respectively. The thickness of poly and the length and width of the seismic mass are good candidates for target-tuning. They have a small effect on SNR but strongly affect the mean. Based on these observations, the sensitivity is hand-tuned. These three tuning parameters are not sufficient to meet target requirements, necessitating the use of beam width, beam length, air gap, and electrode overlap. Ideally, parameters used for tuning SNR shouldn't affect performance and vice-versa. Another challenge is tuning of device dimensions while satisfying design and functional constraints. These constraints cannot be automatically satisfied as in the SPVR approach. Hence, the trial and error-based Taguchi method has its limitations. On the contrary, general statistical methods can include any geometric and function constraints without computation overheads. Specifically, an area constraint is introduced in SPVR, while in Taguchi's method, it is difficult to satisfy this constraint and simultaneously meet the target.

Figure 3 D plots the sensitivity distribution of the optimal design obtained using Taguchi's method. A decrease in sensitivity variance is demonstrated which leads to further yield improvement.

Design Evaluation	Initial	WCD	SPVR	Taguchi
Poly Thickness	2	2.5	2.5	2.5
Beam Width	2	2	2.3	2.5
Beam Length	268	306.7	303.5	261
Overlap Length	110	140.3	206.9	227
Electrode Length	120	142.3	208.9	230
Electrode Width	3	3.7	5.7	3
Air Gap	1.3	2	2.1	2
Mass Length	400	416.3	554.2	692
Mass Width	50	82.6	88.4	142
Finger Number	46	46	46	88
Nominal Sensitivity	3.6mv/g	4.4mv/g	3.8mv/g	4.2mv/g
Sensitivity Mean	4.5mv/g	6.5mv/g	4.9mv/g	5.2mv/g
Sensitivity Deviation	1.3mv/g	2.6mv/g	1.3mv/g	1.1mv/g
Trimming Yield	42.76%	50.48%	63.92%	79.34%

Table 2: Design and Design Evaluation Before and After Each Step of Quality Optimization(sensitivity target=5mv/g) for Accelerometer

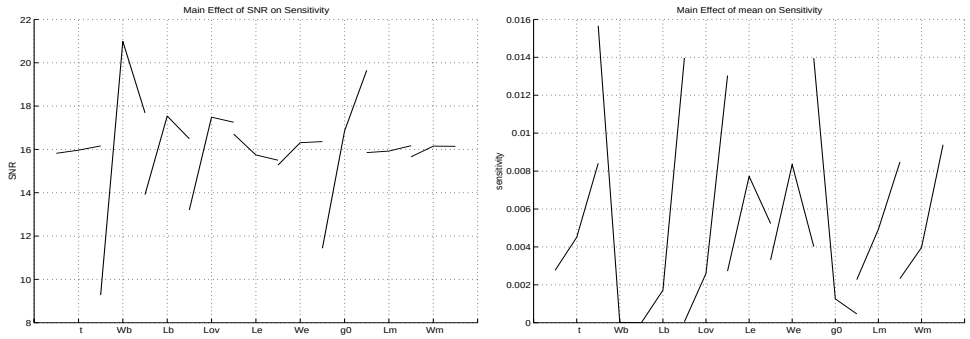

Figure 4: Main Effect of Sensitivity SNR and Mean on Factor Level of Accelerometer Dimension

4 CONCLUSIONS

A three-step technique for quality optimization has been demonstrated. It has been tested on the ADXL50 accelerometer and indicates a 37% yield improvement for a controlled manufacturing process. This initial study makes a uniform etching assumption. Future research efforts are directed towards developing models that relate the etch rate to device geometry as also simultaneous optimization of circuit components.

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