Robust Mask-Layout Synthesis for MEMS

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Abstract

A method for automated mask-layout and process synthesis for MEMS using Genetic Algorithms was proposed by Ma and Antonsson [5]. For a given desired device shape, and several fabrication process choices, this synthesis method will produce one or more mask-layouts and associated fabrication process sequences (which when used can generate shapes close to the desired one). This paper extended the previous work by integrating the robustness of the mask-layout relative to the fabrication variations into the evaluation criteria. By introducing expected variations into the fabrication simulation and making the robustness of the mask-layout part of the evaluation criteria, the stochastic optimization procedure will produce mask-layouts that are least sensitive to these variations, and robust design will be synthesized.

Keywords: MEMS, synthesis, robust design, genetic algorithm

1 INTRODUCTION

Although many remarkable advances in microelectromechanical systems (MEMS) design and fabrication has been made in the past decade, as the complexity of MEMS devices and the scope of MEMS applications increases, the need for structured design methods also increases. Many of the most interesting and useful mechanical devices intrinsically rely on 3-dimensional behavior and 3-dimensional shapes. Complex 3-dimensional shapes can be generated using fabrication procedures such as multiple process wet etching [3], but the mapping from the mask-layout to the final shape is usually non-intuitive and complicated. For a given 3-D device shape, it is difficult for the designer to produce a proper mask-layout as well as correct fabrication procedures by experience and trial and error. An automatic design tool which can automate the shape-to-mask-and-fabrication-process synthesis will be helpful to the development of new MEMS devices.

Previously reported work [5] utilized a genetic algorithm to synthesize mask-layouts and fabrication process. The approach is described as follows. A genetic algorithm iteration loop is constructed to evolve the optimal mask and process sequence. First an initial population of solution candidates (mask-layouts and process parameters) are randomly generated. The fabrication of each mask-layout using the associated process parameters is then simulated by a fabrication simulator to produce a 3-dimensional shape. The performance of each solution candidate is measured through the shape comparison between the produced shape and the user defined final shape. During each evolutionary loop, genetic operations are applied to control the stochastic searching behavior such that the best performing solution candidates are more likely to survive and evolve even better offspring for the next generation. The iteration is stopped when one satisfying solution is found.

Genetic algorithms (GAs [4]) are a global stochastic optimization technique which is based on the adaptive mechanics of natural selection evolution. GAs use two basic processes from evolution: *inheritance*, or the passing of features from one generation to the next, and competition, or *survival of the fittest*, which results in weeding out individuals with bad features from the population. The algorithm maintains a population of solution candidates. and works as an iteration loop. First, an initial population is generated randomly. Then all the individuals in the initial population are evaluated by an objective function measurement program (which is problem specific), and a performance value (also called a fitness value) will be calculated for each individual. Then the whole population goes through genetic operations such as selection, crossover, *etc.*, to form individuals of the next generation. The genetic operations are utilized in such a way that candidate solutions with better performance (higher fitness value) will have more chance to survive and populate.Because of the strong converging characteristics of GA, the new individuals will generally have better performance than the ones in last generation. Such iteration continues until an individual is found whose performance is good enough, and this individual will be taken as the solution.

Some target shapes and synthesized mask-layouts are shown in Figure 1.

2 ROBUST DESIGN

We have developed a Genetic Algorithm approach for MEMS mask-layout and process synthesis, where proper mask-layout and process flow can be automatically generated for given target shape. Here our approach is extended to robust design, and Figure 2 schematically shows how noise factors can be integrated into the design process using our Genetic Algorithm approach to design a solution which is robust to manufacturing variations. In the following, we will describe

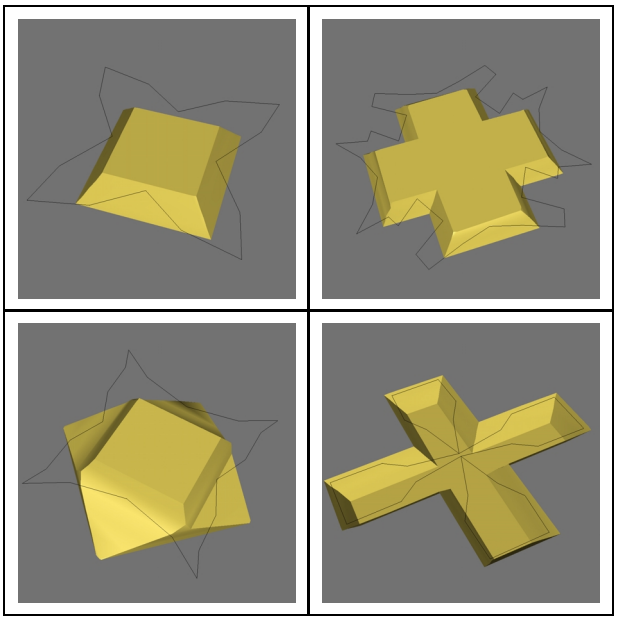

Figure 1: Synthesis examples: etched shapes with mask-layouts shown with black lines

some classic approaches used for robust design, and how to apply GAs for robust design. Finally a robust design scheme for mask misalignment using GA will be described.

2.1 Background

During robust design, a designer seeks to determine the control parameter settings that produce desirable values of the performance mean, while at the same time minimizing the variance of the performance. Robust design, then, is a multiobjective and nondeterministic approach, and is concerned with both the performance mean and the variability that result from uncertainty (represented through noise variables). In this setting, sensitivity analysis is concerned with both the mean and variance of the performance. The performance variation is often minimized at the cost of sacrificing the best performance, and therefore the tradeoff between the aforementioned two aspects cannot be avoided.

Most optimization methods for robust design involve optimization of a statistical estimate of a performance parameter obtained by experiments or computer simulation. In this approach, the design parameters are treated as random variables with assigned probability distributions. The design in question is defined by one or more equations giving a performance parameter as a function of all or some of the design parameters (i.e. a given design point); a large sample of values of the performance parameter may be obtained by repeated sampling of the design parameters from their assigned distributions by use of random number generators. The resulting data can then be used to obtain the expected value and variance of the performance parameter and therefore the value for the statistical estimate at the given design point.

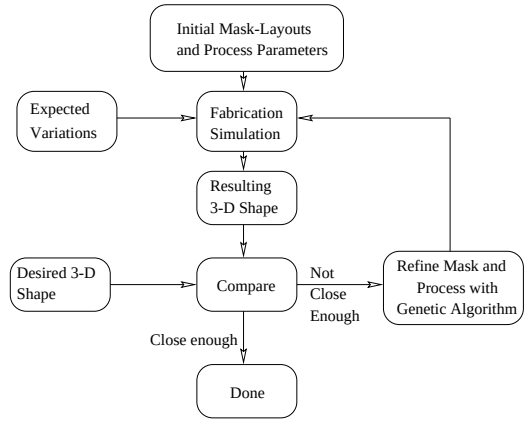

Figure 2: A schematic representation of a genetic algorithm MEMS synthesis technique for robust design.

The optimum design parameter is then obtained at those corresponding to a minimum of the computed estimate, determined by means of some particular non-linear optimization algorithm in the presence of constraints.

In the Taguchi method [6] Signal-to-Noise ratio (S/N ratio) is used as the performance measure (performance statistic), and it usually takes a form of logarithmic function based on the mean square deviation of product responses.

$$S/N \equiv -10\, log[(\sum_{i=1}^{n}(y_i - m)^2)/n] \tag{1}$$

where n is the total number of the experiments, and y_i is performance parameter for an experiment. $y_i = PP(x_j, p_i)$, where PP is the performance parameter being considered, x_j is the design parameter, p_i is noise parameter for an experiment, and m is the desired target value for performance parameter. Since

$$\sum_{i=1}^{n}(y_i - m)^2 = (\mu - m)^2 + \frac{n-1}{n}\sigma^2$$

where μ and σ^2 are the mean and the variance of y, respectively, as computed by

$$\begin{aligned} \mu &= \tfrac{1}{n}\textstyle\sum_{i=1}^{n} y_i \\ \sigma^2 &= \tfrac{1}{n-1}\textstyle\sum_{i=1}^{n}(y_i - \mu)^2 \end{aligned} \tag{2}$$

the S/N increase signifies a decrease in the average results or improved consistency form one unit to another, and a combined improvement in the mean result and a reduction in the variability will result in the greatest S/N increase.

2.2 Genetic Algorithms for Robust Design

To extend the applications of GAs to domains that have a noisy environment and require detection of robust solutions, schemes combining GAs and robustness evaluation techniques

and robust solution searching techniques have been introduced [2]. GAs with noisy fitness functions and GAs exploring hyper-rectangle design regions instead of design points in traditional GAs have been studied. For our mask-layout and process synthesis problem, we applied a robust design scheme similar to the one introduced by Tsutsui, called Genetic Algorithms with Robust Solution Searching Scheme (GA/RS^3) [7], which is outlined below.

In a GA, if $G = (g_1, g_2, ..., g_m)$ is a genotypic string for an individual and $P = (p_1, p_2, ..., p_m)$ is the corresponding phenotypic parameter vector, $f(P)$ the evaluation function for fitness, instead of calculating the fitness value of the individual as $f(P)$, we use an evaluation function of the form $f(P+\Delta)$, where $\Delta = (\delta_1, \delta_2, ..., \delta_m)$ is a random noise vector. The solutions thus determined are expected to be more robust against perturbations or noise having the appropriate tested distribution. It should be noted that adding noise in the form $f(P + \Delta)$ may appear like a mutation operation on a real-valued coding, but actually it is operationally different from mutation, since the noise is added only to the phenotype and it does not have any direct effect on individual genotypes. The perturbations are used only for judging the quality of a solution and for selection.

2.3 Robust Design for Mask Misalignment

This section describes the implementation details of a robust design for mask misalignment.

For commercial silicon wafers, the alignment accuracy (between the flat and the crystal orientation) is usually around $\pm 1^\circ$ [8], additionally, the mask may not be perfectly aligned to the wafer flat. This misalignment can affect the precision of shapes fabricated. For example, the size of diaphragms formed after etching through a $500\mu m$ thick silicon safer can vary by $50\mu m$ if the accuracy of the alignment is of the order of 1° [1], [8]. For this application, the optimum mask-layout and process used to fabricate the target shape is searched assuming perfect alignment, and in actual fabrication, the misalignment of mask-layout, is the noise factor which affects the quality of the fabricated device, and this variation of mask-layout misalignment can be taken as the uncontrolled variation when the robust design is conducted.

When conducting the robust design synthesis for mask misalignment, the S/N ratio in Taguchi method is used as the performance statistic, and the sampling and searching scheme of GA/RS^3 is borrowed. For this problem, the mask-layout misalignment is considered to be uncontrollable noise with Gaussian distribution with $\mu = 0$ and $\sigma = 1^\circ$. For every individual in a generation, a series of randomly generated misalignments are assigned to the mask-layout before the fitness values are calculated, and then the fitness values are used to construct the S/N ratio. This ratio is taken as the performance statistic to guide the search for optimum design point, and the optimum mask-layout and process found will have high robustness relative to mask misalignment. The schematic model of the fitness evaluation in our robust synthesis is shown in Figure 3.

```
for each generation with population G_1, G_2, ..., G_N:
{
    Decode each genotype G_i to produce corresponding phenotype X_i;
    for(each phenotype X_i (mask-layout))
    {
        S/N = 0;
        for(j = 0; j <= n; j++)
        {
            Randomly generate mask misalignment noise Δ_j
                according to distribution;
            Y_i = X_i rotated Δ_j degrees;
            Evaluate fitness_i = f(Y_i);
            S/N += fitness_i/n;
        }
        S/N = -10log(S/N);
        fitness_i = S/N;
    }
}
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Figure 3: Schematic model of fitness evaluation

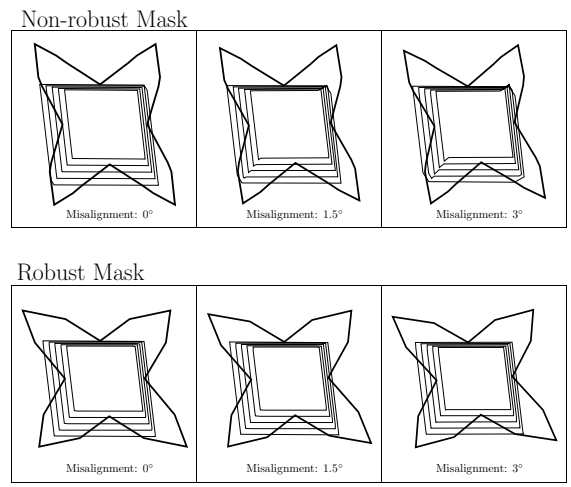

Figure 4: Comparison of robust synthesis and non-robust synthesis

Given a mesa (peg) as the target shape, the robust design is conducted and the synthesis result is compared with the result from synthesis without considering mask misalignment (here called non-robust synthesis). Figure 4 shows the comparison of results from the robust synthesis and the non-robust synthesis. The first row shows the mask-layout from robust synthesis and the fabricated shapes when the mask misalignments are 0°, 1.5°, and 3°. The second row is for non-robust synthesis. Both mask-layouts generate shapes close to the target shape (mesa) when perfectly aligned (0° misalignment), but when the misalignment increases, the superiority of the mask-layout from robust synthesis can be easily observed.

To statistically demonstrate that the result from robust synthesis does have higher robustness, both optimum mask-layouts synthesized from the robust synthesis and the non-robust synthesis are tested with a series (600 experiments) of

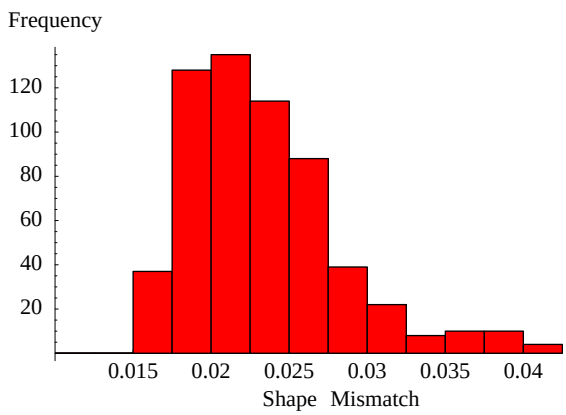

Figure 5: Histogram of fitness distribution for NON-ROBUST synthesis result

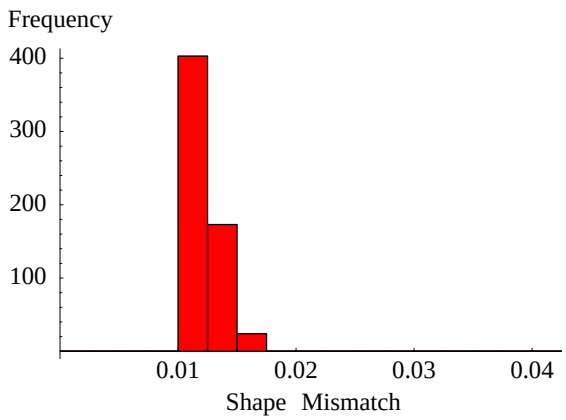

Figure 6: Histogram of fitness distribution for ROBUST synthesis result

randomly generated misalignment noises according to Gaussian distribution with $\mu = 0$ and $\sigma = 1°$. The fitness values (in this application, the shape mismatch values between the simulated shape and the target shape) acquired are used to construct the histograms of the shape mismatch distribution for both masks under Gaussian distributed misalignment noise, shown in Figure 5 and Figure 6. Figure 5 is for the mask from non-robust synthesis, and Figure 6 is for the mask obtained from the robust synthesis. X axis is the shape mismatch value, and Y axis is the experiment frequency. The smaller mean and smaller deviation for the shape mismatch distribution for the robust synthesis result can be observed from the histograms. Also simulations are performed for both masks with different misalignment values, and Figure 7 shows the shape mismatch vs. mask misalignment for both masks. Obviously the mask from robust synthesis has more robust performance.

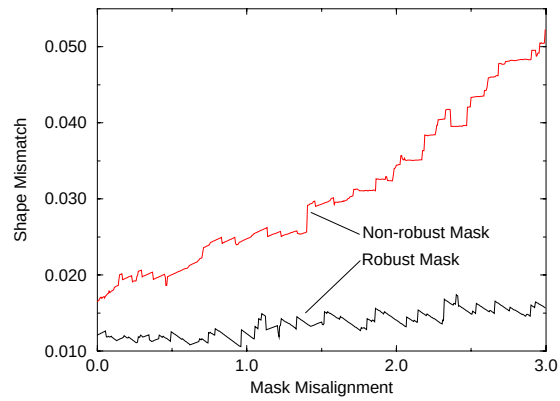

Figure 7: Shape mismatch vs. mask misalignment for both masks

3 CONCLUSIONS

A robust design method for MEMS mask-layout synthesis combining a genetic algorithm and forward fabrication simulation is introduced, and an application of the method is conducted to design mask-layouts robust to mask misalignment. Other fabrication and process variations (*e.g.*, etch rate variation) can be introduced into the fabrication simulation, and by combining these variations into the synthesis iteration loop, the stochastic optimization will produce mask-layouts and process sequences that are least sensitive to these variations.

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