Evolutionary Synthesis of Micromachines Using Supervisory Multiobjective Interactive Evolutionary Computation

Raffi Kamalian[1], Ying Zhang[2], Hideyuki Takagi[1], and Alice M. Agogino[2]

[1] Faculty of Design, Kyushu University,
Fukuoka 815-8540, Japan
`{raffi, takagi}@design.kyushu-u.ac.jp`
[2] BEST Lab, 6102 Etcheverry Hall, University of California, Berkeley,
CA 94720, USA
`{yzh, agogino}@berkeley.edu`

Abstract. A novel method of Interactive Evolutionary Computation (IEC) for the design of microelectromechanical systems (MEMS) is presented. As the main limitation of IEC is human fatigue, an alternate implementation that requires a reduced amount of human interaction is proposed. The method is applied to a multi-objective genetic algorithm, with the human in a supervisory role, providing evaluation only every n^{th}-generation. Human interaction is applied to the evolution process by means of Pareto-rank shifting for the fitness calculation used in selection. The results of a test on 13 users shows that this IEC method can produce statistically significant better MEMS resonators than fully automated non-interactive evolutionary approaches.

1 Introduction

In this paper we present a new method of synthesis utilizing human interaction to augment the use of evolutionary computation to generate resonating microelectromechanical systems (MEMS). MEMS, also known as Micromachines are electromechanical mechanisms and transducers created using IC microfabrication techniques. In this paper we use the example application of the design of a resonating mass, a simple MEMS example that can be extended to the design of MEMS-based RF filters or inertial sensors.

1.1 MEMS Evolutionary Synthesis

An evolutionary MEMS synthesis tool has been presented in [1], [2]. A multi-objective genetic algorithm (MOGA)[3], as well as simulated annealing (SA) [4] have been used as an evolutionary computation method for the design of a variety of MEMS test applications, including the design of electrostatic actuators [5],[6], accelerometers and vibrating rate gyroscopes [7].

A MEMS simulator is used by the evolutionary algorithm to predict the performance of the candidate design. Unfortunately to remain tractable for the evolutionary

D.S. Yeung et al. (Eds.): ICMLC 2005, LNAI 3930, pp. 428 – 437, 2006.

process, simplified, reduced order modelling tools can not predict the sensitivity of a design to fabrication uncertainty and do not include the effects of certain design features on performance. A fabrication and characterization study (Fig. 1) has shown that these sensitivities can dramatically affect the quality of the solutions generated. Many of these potential problems are clearly visible to a human user visually observing the design layout, but they would be difficult, if not impossible, to mathematically model and simulate in software and incorporate into a flexible MEMS synthesis program. A human's opinion, based on their experience, expert domain knowledge or simple preference can not be easily coded into a numerical fitness function. Therefore we developed a human-interactive MEMS design tool to allow the inclusion of this human knowledge.

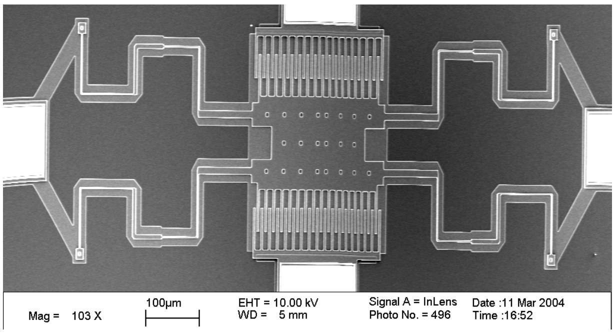


Fig. 1. Example of resonating micromachine design generated by our MOGA tool that has been fabricated and characterized. The center mass is approximately 0.2mm wide.

1.2 Interactive Evolutionary Computation

Interactive Evolutionary Computation (IEC) is a method for optimizing a system using subjective human evaluation as part of the optimization process. It is well suited for optimizing systems whose evaluation criteria are preferential or subjective, such as graphics, music and design, and systems that can be evaluated based on expert's domain knowledge. Fields in which this technology has been applied includes graphic arts and animation, 3-D CG lighting, music, editorial design, industrial design, facial image generation, speech and image processing, hearing aid fitting, virtual reality, media database retrieval, data mining, control and robotics, food industry, geophysics, education, entertainment, social system, and others [8].

In [9], an initial method of using IEC to further hone MEMS designs generated by a MOGA was presented. In this case output from the automated MOGA tool was used to draw the initial designs for IEC. This allowed the human user to further evolve the output into designs that better met their expert opinions and goals. A single objective genetic algorithm used the user's evaluation for fitness ranking. A user study presented shows that the combination of the automated and human interactive can produce better designs than by simple automated evolutionary synthesis alone. A simple example of a human's evaluation of two MEMS resonating mass designs can be seen in Fig. 2.

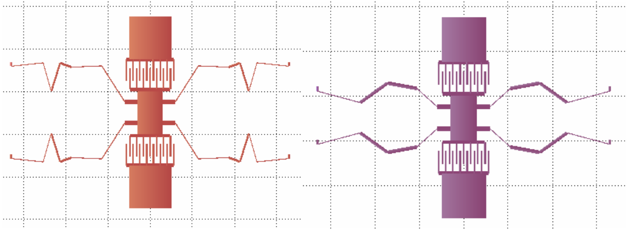


Fig. 2. (a) left: MEMS resonator design produced by Non-interactive MOGA, given a poor score by a user due to potential stress concentrations in the legs. (b) right: High scoring MOGA+IEC design generated by the same user, free of perceived negative traits.

One of the limitations of IEC that does not exist in conventional, non-interactive EC, is that the humans evaluating the fitness of designs suffer from fatigue, and therefore we would like to search out new methods of better matching the capabilities of the human and the computer to exploit their strengths and minimize their weaknesses.

Based on the observations of the user study, presented in [10], we developed a new version of EC with human interaction. This new implementation differs in that the human's participation is more in a supervisory role, utilizing the tireless computation power of computer but still allowing the human to input their expert knowledge and visual perception of a design when desired.

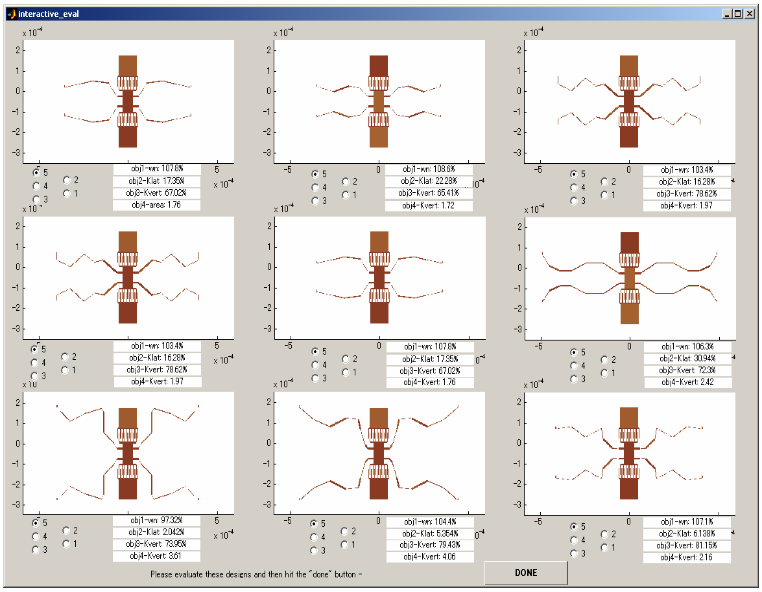
In this paper we present a description of the new interactive EC tool for MEMS, as well as the results from a user study to verify the ability of the tools to produce better output, compared to our original non-interactive MOGA tool.

2 Alternate MEMS IEC Implementation

The original IEC MEMS synthesis, as presented in [9], used a population size of 27,and evaluated up to 10 generations. A human evaluated each individual of each generation based on the layout as well as the performance predicted by a simulator tool. The score given ranged from 1 to 5 and was selected by the user by a mouse click (see Fig. 3 for user interface). The human user generated a single subjective score based on his/her opinion of the shape as well as the performance in four objectives, in essence mentally computing a weighting function to generate a score with a range of 1 to 5.

A user study of 11 test subjects showed that IEC produced statistically significant better results than non-interactive evolutionary synthesis. With up to 270 human evaluations required, human fatigue was a concern and limited the number of generations the evolution could continue.

In our original user study, we identified two interesting types of reactions from the human when scoring the individuals via IEC. When humans detected design features they did not like they generally immediately scored that design very low regardless of the objective performance of that individual. This situation can be described as a human-applied constraint violation, or as the human attempting to screen the population by culling (or 'killing off') designs of which they disapprove.



● 5 ○ 4 ○ 3 ○ 2 ○ 1
obj1-wn: 107.8%
obj2-Klat: 17.35%
obj3-Kvert: 67.02%
obj4-area: 1.76

● 5 ○ 4 ○ 3 ○ 2 ○ 1
obj1-wn: 108.6%
obj2-Klat: 22.28%
obj3-Kvert: 65.41%
obj4-Kvert: 1.72

● 5 ○ 4 ○ 3 ○ 2 ○ 1
obj1-wn: 103.4%
obj2-Klat: 16.28%
obj3-Kvert: 78.62%
obj4-Kvert: 1.97

● 5 ○ 4 ○ 3 ○ 2 ○ 1
obj1-wn: 103.4%
obj2-Klat: 16.28%
obj3-Kvert: 78.62%
obj4-Kvert: 1.97

● 5 ○ 4 ○ 3 ○ 2 ○ 1
obj1-wn: 107.8%
obj2-Klat: 17.35%
obj3-Kvert: 67.02%
obj4-Kvert: 1.76

● 5 ○ 4 ○ 3 ○ 2 ○ 1
obj1-wn: 106.3%
obj2-Klat: 30.94%
obj3-Kvert: 72.3%
obj4-Kvert: 2.42

● 5 ○ 4 ○ 3 ○ 2 ○ 1
obj1-wn: 97.32%
obj2-Klat: 2.042%
obj3-Kvert: 73.95%
obj4-Kvert: 3.61

● 5 ○ 4 ○ 3 ○ 2 ○ 1
obj1-wn: 104.4%
obj2-Klat: 5.354%
obj3-Kvert: 79.43%
obj4-Kvert: 4.06

● 5 ○ 4 ○ 3 ○ 2 ○ 1
obj1-wn: 107.1%
obj2-Klat: 6.138%
obj3-Kvert: 81.15%
obj4-Kvert: 2.16

Please evaluate these designs and then hit the "done" button -

Fig. 3. User interface of original IEC MEMS synthesis tool

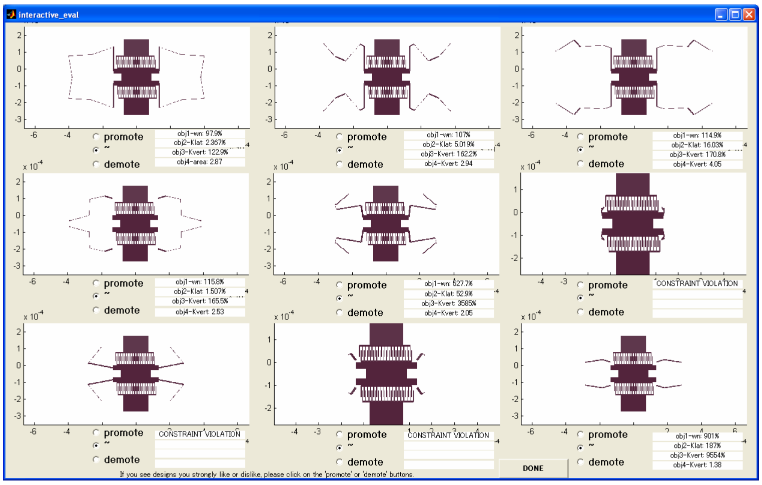
The second type of behavior was the opposite, where a design feature of interest prompted the human to score a design highly despite poor performance in the objective space. In a normal GA, this design would not be likely to pass along its features to subsequent generations, but IEC allows the human to give it a 'stay of execution', so that its features are allowed to propagate to future generations of the design.

2.1 Improved IEC Approach

We chose to build upon these observations to create a version of IEC where the human's interactions are limited to these two types of action. We developed an interface (see Fig. 4) where the human can chose to give either a *promote* (positive) or *demote* (negative) reaction to each design presented. This human evaluation is then used to shift the ranking of the design accordingly. Our MOGA implementation uses Pareto ranking to handle multiobjectives, which is then used by a roulette wheel function for selection for genetic operations. Therefore the human interaction is used to adjust the Pareto ranking of a design (upwards or downwards). The default choice is to not take any action for a design, leaving its Pareto ranking unaltered.

In practice this means a design not on the Pareto frontier may be artificially promoted to the Pareto dominant set by the human, which will allow it to be passed to the next generation by elitism, and make it much more likely to be chosen as a parent for crossover. Likewise a Pareto frontier design might be demoted to a lower rank by the human, making it less likely to pass along its traits in the future.

It should be noted that as we are adjusting the Pareto ranking, which is used for roulette wheel (probabilistic) selection, the human's actions differ slightly from a



○ promote ● ~ ○ demote
obj1-wn: 97.9%
obj2-Klat: 2.367%
obj3-Kvert: 122.9%
obj4-area: 2.87

○ promote ● ~ ○ demote
obj1-wn: 107%
obj2-Klat: 5.019%
obj3-Kvert: 162.2%
obj4-Kvert: 2.94

○ promote ● ~ ○ demote
obj1-wn: 114.9%
obj2-Klat: 16.03%
obj3-Kvert: 170.8%
obj4-Kvert: 4.05

○ promote ● ~ ○ demote
obj1-wn: 115.8%
obj2-Klat: 1.507%
obj3-Kvert: 165.5%
obj4-Kvert: 2.53

○ promote ● ~ ○ demote
obj1-wn: 527.7%
obj2-Klat: 52.9%
obj3-Kvert: 3585%
obj4-Kvert: 2.05

○ promote ● ~ ○ demote
CONSTRAINT VIOLATION

○ promote ● ~ ○ demote
CONSTRAINT VIOLATION

○ promote ● ~ ○ demote
CONSTRAINT VIOLATION

○ promote ● ~ ○ demote
obj1-wn: 901%
obj2-Klat: 187%
obj3-Kvert: 9554%
obj4-Kvert: 1.38

If you see designs you strongly like or dislike, please click on the 'promote' or 'demote' buttons.

Fig. 4. User interface of new IEC MEMS synthesis tool

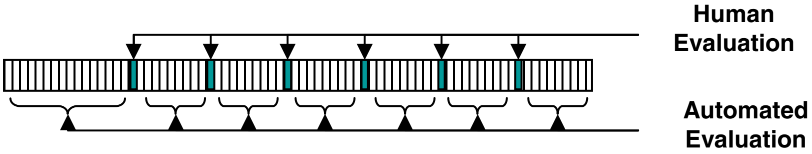


Fig. 5. Schematic of interspresed human interaction in automated evolutionary synthesis

simple absolute screening approach. It should also be noted that the human's interaction can be applied as little or as much as desired. Generally we find that users have a strong opinion (positive or negative) only a relatively small percentage of the time. Therefore this approach requires less activity (through scoring via the graphical user interface (GUI)) than the previous IEC MEMS tool.

This method is also unique in that it combines IEC with multiobjective GA. With few exceptions, [8],[11] most IEC applications are limited to single objective optimization problem, this implementation allows a human to interact with a MOGA without needing to combine objectives into a weighted sum (either explicitly via a formula or implicitly within the user's head).

Another unique aspect of our proposed alternate method is that the level of human interaction is flexible; if the human were to not score any designs, the tool becomes identical to the automated MOGA, using the unmodified Pareto ranking. In this respect, we have chosen a method where the human interaction for evaluation occurs only every n^{th}-generation (see Fig. 5). Automated evolution with occasional human 'review' combines the tirelessness and speed of the computer with the more 'expensive' (in terms of time and fatigue) opinion of the human.

The time and attention required by the human is further reduced by not displaying physically invalid designs in the interactive phase. As much as half of the population at any given point may violate a validity constraint such as those introduced to remove designs that are not physically realizable in the MEMS fabrication environment (e.g., no crossing of legs, minimum distances between parts, etc.) By removing these designs from human consideration, they can focus their attention exclusively on meaningful designs, delaying the onset of fatigue. In practical terms, this means the user's effort can be focused on producing more better designs rather than being expended looking at invalid designs.

3 Experiment

To verify the success of the tool, we performed a user test of 13 student volunteers using the tool. The design of a symmetric, four legged resonating mass was used as a test problem. Four objective goals are set for the synthesis: ω_r (10,000Hz), area (minimized), lateral stiffness (100 N/m) and vertical stiffness (0.5 N/m). The problem formulation, geometrical bounds, constraints and objectives are identical to those used in [7],[9],[12].

Table 1. Settings for improved IEC user test

Property	Setting
Population Size	80
Generations	80
Interval for human interaction	Every 10^{th} generations
Starting point for human interaction	20^{th} generation
Total number of human interaction generations	6 (20,30,40, 50,60,70^{th} generations)

3.1 User Test Setup

The settings and parameters for the Interactive evolutionary implementation used in this paper are presented in Table 1. The human evaluation phase occurs 6 times over the course of the 80 generation test. As our initial population is randomly generated from scratch, human interaction is not initiated until the 20th generation to give the GA the opportunity to first converge towards the objective goals before the human expertise is applied. Each generation of human interaction, approximately five screens worth of designs (up to 9 designs per screen) are displayed, for a total of approximately 300 designs presented to the human throughout the course of the synthesis, of which the human may only actually chose to adjust the ranking of a fraction of these.

3.2 MEMS Synthesis Quality Metric

Design synthesis [13] relies on the ability to accurately predict in advance the performance of a proposed design. Through a study of MEMS synthesis designs fabricated and characterized, we have found that certain types of design features lead to inaccurate predictions using the tractable MEMS simulation tools capable of being used in an evolutionary computation algorithm at the present time.

The characterization test of fabricated evolutionary synthesis output reveals two important factors that dramatically impact the accuracy of some of the designs generated [7]. When fabricated, these designs' performance differ dramatically from the predicted performance in the most critical objective, the resonant frequency. These designs are susceptible to one or both of two phenomenon - simulator deficiencies and fabrication variation.

Finite Element Modeling (FEM) has the ability to very accurately predict the performance of a resonating mass, but requires a significant time to simulate. We therefore use a simplified nodal analysis-based simulator, which also has the benefit of easier integration with our discretized component-based evolutionary encoding. The open source simulation tool SUGAR [14] is used as the evaluation engine, but it lacks the ability to accurately model the end conditions of beam elements. This leads to a loss of accuracy in certain geometrical configurations (such as thin-thick junctions at acute angles).

Likewise, the presence of uncharacterized process variation can dramatically impact the performance of a design when fabricated. Currently in most MEMS foundries, there is no characterization or prediction of the level of residual stress that exists in material layers. This residual stress can dramatically impact the resonant frequency for certain geometrical configurations as well (such as designs with a very high lateral stiffness, large anchor width, etc).

In [12] a performance metric for these two deficiencies was presented. The first was a 'simulation error percentage', the percentage difference between the frequency predicted by SUGAR and that predicted by the FEM tool ANSYS. The second metric was 'fabrication error percentage', the percent change in the frequency with and without a typical amount of compressive residual stress included. (Note, a 5 MPa compressive stress was used for this study). This percentage is equivalent to the sensitivity of a particular design to the presence of residual stress. For more information on these metrics and their sources, please refer to [12].

The goal of the user study of our new IEC tool is to test whether the IEC output has a lower amount of simulation error on average than that of the automated MOGA. We also would like to show that IEC has less sensitivity to residual stress, (which is generated in the fabrication process) than the automated designs. The absolute magnitude of these numbers is not important, rather we focus on their relative improvement and statistical variation.

An analysis of variance (ANOVA) test [15] is used to measure the level amount of variation between two groups and tell us if it is statistically significant. This test is applied to compare the two groups of designs for each of the two metrics to tell if there is a significant difference between the two methods

3.3 Results

Employing a similar testing strategy as [10] and [12], we take the best two designs produced by each synthesis run that are within 500 Hz of the goal of 10 kHz. Each of these is evaluated in SUGAR, and the FEM tool ANSYS. The simulator error percentage and fabrication error percentage are calculated. These results are compared to the results of 10 runs of the automated synthesis program - identical settings and code, except no human interaction is used.

The average error as well as the standard deviation is presented in Table 2. In the case of both metrics, the IEC results perform better (have less sensitivity to these factors) than the automated version. The standard deviation amongst the human inter

Table 2. Comparison of results of improved IEC user test and automated EC for 4-objective MEMS resonator test problem. The IEC method presented in this paper performs better than the baseline, non-interactive EC method for both metrics.

	Improved IEC (26 designs)	Automated EC(20 designs)
Simulator Error Percentage		
Average	0.3%	3.3%
Std. dev	4.7%	2.7%
ANOVA P-value	P=0.016 (*98% significance*)	
Fabrication Error Percentage		
Average	58%	73%
Std. dev	15%	23%
ANOVA P-value	P=0.014 (*98% significance*)	

action results is higher for the simulator error, which can possibly be attributed to the difference in the quality of the interaction by the various users in the study. Whereas the automated synthesis tool is generally more consistent from run to run, despite producing less desirable designs. The results of the ANOVA test are also presented in Table 2. They confirm that there is a statistically significant difference in the quality of output for both factors.

As user fatigue is difficult to quantify, we can not make conclusions about the success of this system compared to our previous IEC MEMS program or other implementations of IEC in terms of user fatigue. However a general idea of fatigue can be drawn by looking at the number of actions required to execute the synthesis run (in this case mouse clicks on radio buttons in the graphical user interface).

In the new IEC implementation, the user need only act approximately 60-90 times per synthesis run (although our observation is that some users actually score much more than this at their choice). Even for a user who rates more than a few designs per screen, this compares well against the 240-270 actions required in the previous IEC implementation presented in [9]. Similarly the average time required for one run of the IEC presented in this paper is shorter than the time required for the previous implementation, approximately 45 minutes per user versus one hour per user, respectively.

4 Conclusion / Future Work

This work presents an initial trial of a new implementation of human interaction for evolutionary MEMS design synthesis. Our user study shows that the quality of the output is superior to the output of a non-interactive evolutionary design program.

More testing to directly compare the performance of this new IEC to the previous IEC implementation is needed before the benefits of the alternate methods can be fully gauged; this requires another user study that compares the performance of two methods analytically. The challenge is to develop a fair test that can compare the quality of the output produced by the two methods when they require an equivalent amount of effort (fatigue) from the human, or to compare the amount of effort required to produce the equivalent quality output. We would then validate the results of this study by fabricating and characterizing the output produced by this implementation and comparing the real world performance with other designs generated by other interactive and non-interactive synthesis implementations.

Finally, we intend to apply this method to the design of other MEMS devices, such as MEMS inertial sensors. Additionally it would be interesting to apply this method to the device or layout design in other engineering domains as well, such as the design of circuits, building structures, HVAC, etc.

A promising extension of this method is to include a human predictor to either assist or partially replace the human interaction. For example a neural network could be trained either before or during evolution to predict which designs might warrant a 'promote' or 'demote' score. This predictor could anticipate the users preferences for all the designs in the IEC UI; the user need only review these predictions and correct any mistakes. This could further reduce the amount of physical and mental effort required, allowing for larger population sizes or more generations of evolution. An alternate approach utilizes a neural network to evaluate a much larger population on behalf of the user, while the user only occasionally provides a small amount of additional evaluation to improve the training of the neural network. We are currently investigating these approaches and testing their implementation for application to MEMS synthesis.

Acknowledgements

This research was conducted, in part, through NSF grant CCR-DES/CC-0306557. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

1. Zhou, N., Zhu, B., Agogino, A. M. and Pister, K. S. J.: Evolutionary Synthesis of MEMS MicroElectronicMechanical Systems Design, Intelligent Engineering System through Artificial Neural Networks Proceedings of the Artificial Neural Networks in Engineering (ANNIE2001), (2001) 197-202
2. Zhou, N., Agogino, A. M., and Pister, K. S. J.: Automated Design Synthesis for Micro-Electro-Mechanical Systems (MEMS), Proceedings of ASME Design Automation Conference, (2002)
3. Goldberg, D. E.: Genetic Algorithms in Search, Optimization and Machine Learning, Addison-Wesley Longman, Boston, MA, (1989)
4. van Laarhoven, P. J. M., Aarts, E. H. L.: Simulated Annealing: Theory and Applications, Reidel Publishing, Dordrecht, Holland, (1987)
5. Zhou, N.: Simulation and Synthesis of Microelectromechanical Systems, Doctoral Thesis, UC Berkeley, (2002)
6. Kamalian, R., Zhou, N., Agogino, A.M.: A Comparison of MEMS Synthesis Techniques, Proceedings of the 1st Pacific Rim Workshop on Transducers and Micro/Nano Technologies, Xiamen, China, (2002), 239-242
7. Kamalian, R.: Evolutionary Synthesis of MEMS, Doctoral Thesis, UC Berkeley, (2004)

8. Takagi, H.: Interactive Evolutionary Computation: Fusion of the Capacities of EC Optimization and Human Evaluation, Proceedings of the IEEE, vol. 89, no. 9, (2001), 1275-1296
9. Kamalian, R., Takagi, H., Agogino, A.M.: Optimized Design of MEMS by Evolutionary Multi-objective Optimization with Interactive Evolutionary Computation, Proceedings of GECCO 2004, Genetic and Evolutionary Computation Conference, (2004), 1030-1041
10. Kamalian, R., Takagi, H., Agogino, A.M.: The Role Of Constraints and Human Interaction in Evolving MEMS Designs: Microresonator Case Study, Proceedings of DETC'04, ASME 2004 Design Engineering Technical Conference, Salt Lake City, UT, (2004)
11. Singh, A., Minsker, B. S., Takagi, H.: Interactive Genetic Algorithms for Inverse Groundwater Modeling, American Society of Civil Engineers (ASCE) Environmental & Water Resources Institute (EWRI) World Water & Environmental Resources Congress 2005, Anchorage, AK, (2005)
12. Kamalian, R., Agogino, A.M.: Improving Evolutionary Synthesis of MEMS through Fabrication and Testing Feedback, IEEE SMC 2005, IEEE Conference on Systems, Man and Cybernetics, (2005)
13. Antonsson, E. K., Cagan, J. (eds): Formal Engineering Design Synthesis, Cambridge University Press, Cambridge, (2001)
14. SUGAR: Simulation Research for MEMS, http://bsac.eecs.berkeley.edu/cadtools/sugar/sugar/
15. ANOVA: ANalysis Of VAriance between groups, http://www.physics.csbsju.edu/stats/anova.html