Proceedings of the Fourth International Conference on Machine Learning and Cybernetics, Guangzhou, 18-21 August 2005

REDUCED HUMAN FATIGUE INTERACTIVE EVOLUTIONARY COMPUTATION FOR MICROMACHINE DESIGN

RAFFI KAMALIAN[1], YING ZHANG[2], HIDEYUKI TAKAGI[1], ALICE M. AGOGINO[2]

[1]Faculty of Design, Kyushu University, Fukuoka 815-8540, Japan
[2]Berkeley Experts Systems Technology Lab, University of California Berkeley, Berkeley, CA, 97420, USA
E-MAIL: raffi@design.kyushu-u.ac.jp, yzh@berkeley.edu, takagi@design.kyushu-u.ac.jp, agogino@berkeley.edu

Abstract:

This paper presents a novel method of using Interactive Evolutionary Computation (IEC) for the design of Microelectromechanical Systems (MEMS). A key limitation of IEC is human fatigue. Based on the results of a study of a previous IEC MEMS tool, an alternate form that requires less human interaction is presented. The method is applied on top of a conventional multi-objective genetic algorithm, with the human in a supervisory role, providing evaluation only every *nth*-generation. Human interaction is applied to the evolution process by means of Pareto-rank shifting, which is used for the fitness calculation used in selection. Results of a test of 13 users shows that this IEC method can produce statistically significant better MEMS resonators than non-interactive evolutionary synthesis.**

Keywords:

Evolutionary Computation; Interactive Evolutionary Computation; IEC; MOGA; Human Interaction; CAD; MEMS; Micromachines

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. The resonating mass structure is a simple MEMS example that can be extended to the design of MEMS-based RF filters or inertial sensors.

An evolutionary MEMS synthesis tool has been presented in [1],[2]. A multiobjective 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].

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].

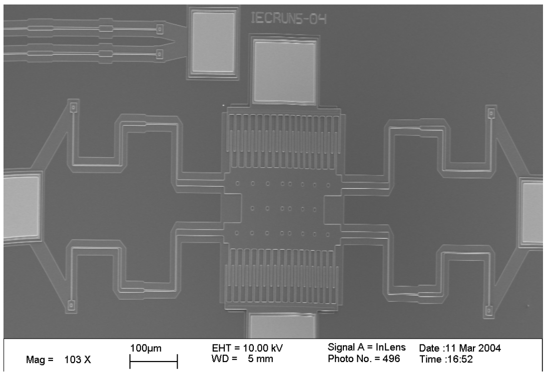

Figure 1. Example of resonating micromachine design generated by MOGA tool that has been fabricated and characterized. Center mass is approximately 0.2mm wide.

In the case of MEMS simulation, tractable simulation tools can not predict the sensitivity of a design to fabrication uncertainty or and do not include the effects of certain design features on performance. A fabrication and characterization study [7] (see Figure 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,

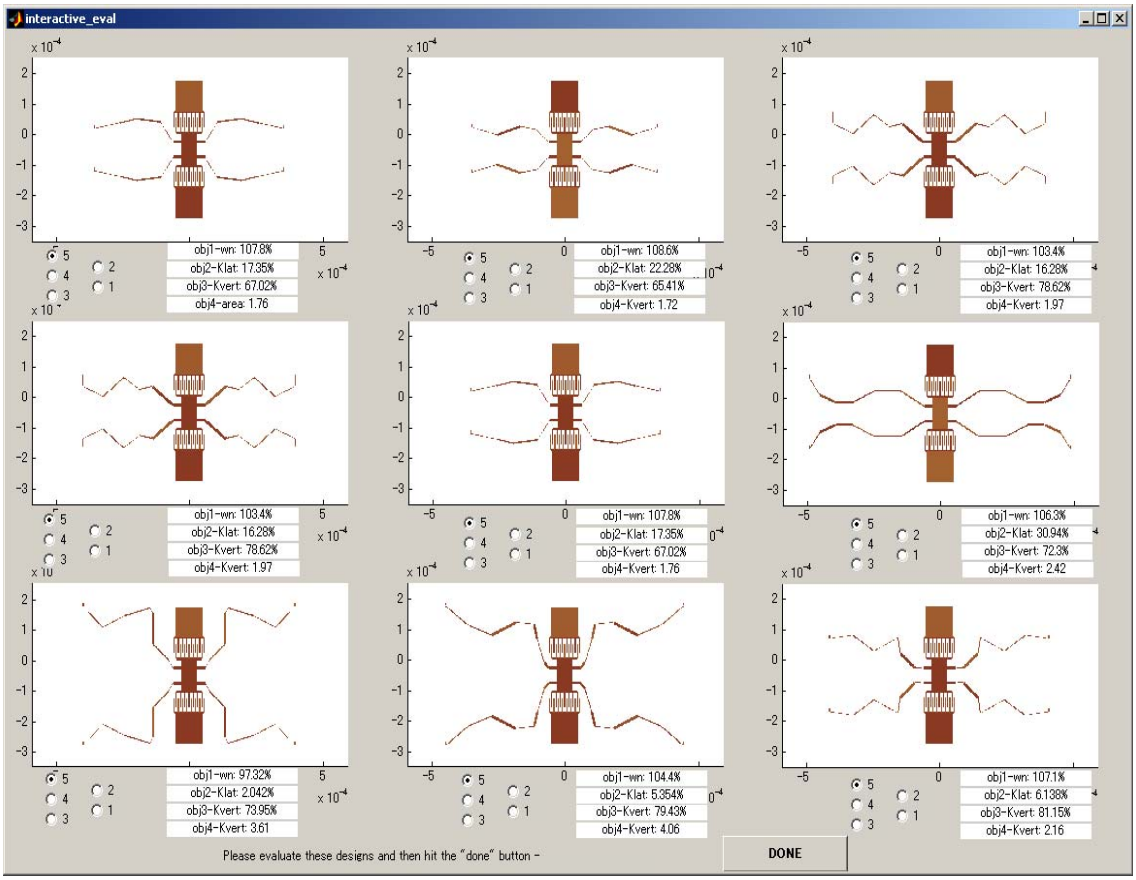

Figure 2. User interface of original IEC MEMS synthesis tool.

to mathematically model and simulate in software and incorporate into a flexible MEMS synthesis program. Therefore we developed an IEC based MEMS design tool to allow the inclusion of this human knowledge.

In [9], an initial method of using IEC to further hone 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 MOGA output into designs that better met their expert opinions and goals. 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.

One of the limitations of IEC that does not exist in 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 IEC MEMS design implementation

The original IEC MEMS synthesis, presented in [9] used a population size of 27, evaluated up to 10 generations. A human evaluated each individual each generation based on the layout as well as the performance prediction by a simulator tool. The score given ranged from 1 to 5, chosen by mouse click (see Figure for user interface). The

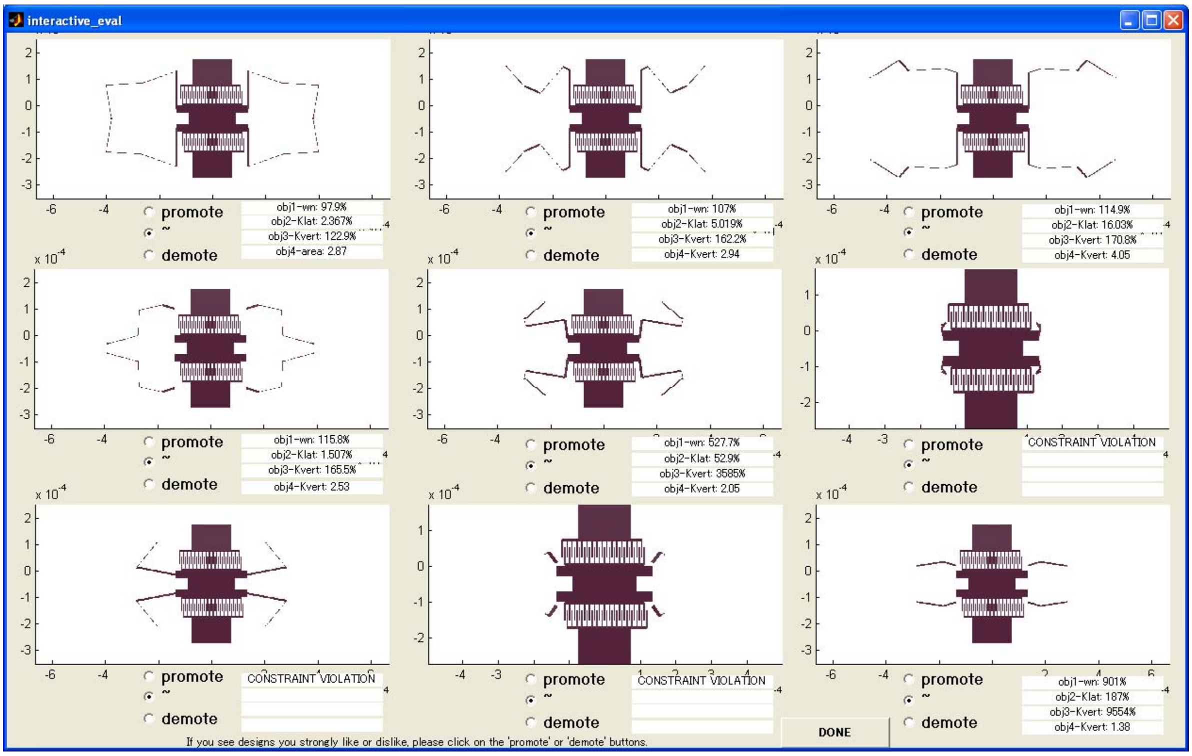

Figure 3. User interface of new IEC MEMS synthesis tool.

human must generate a single subjective score based on their opinion of the shape as well as the performance in four objectives, in essence mentally computing a weighting function to generate a 1 through 5 score.

A user study of 11 test subjects showed that IEC produced statistically significant better results than non-interactive evolutionary synthesis. But at 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 reaction 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 they disapprove of.

The second type of behavior was the opposite, where a design feature of interest might prompt 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 the following generations, but the human has chosen to give it a 'stay of execution' to a design, so that its features will be allowed to propagate to the future generations.

We chose to build upon these observations and create a version of IEC where the human's interactions are limited to these two types of behavior. We developed an interface (see Figure) 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 according. 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).

In practice this means a design not on the Pareto frontier may be artificially promoted to the Pareto 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 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 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.

Human interaction is not necessary for the function of the evolutionary synthesis (if the human were to not score any designs, the tool becomes identical to the automated MOGA, using the unmodified Pareto ranking). Additionally, we have chosen a method where the human interaction for evaluation occurs only every n^{th}-generation (see Figure). This 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 the constraint that no design can contain legs that cross each other, as this design is not physically realizable in the MEMS fabrication environment. By removing these designs from human consideration, they can focus their attention only on meaningful designs, delaying the onset of fatigue.

3. Experiment

3.1. User Test Setup

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 objectives 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],[11].

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 does not incur 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.

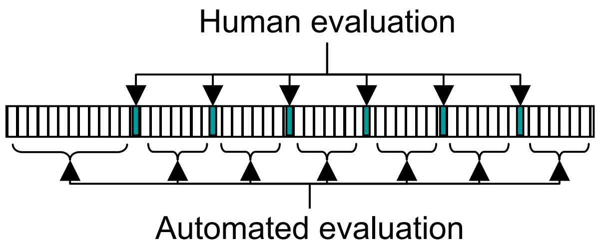

Figure 4. Schematic of interspresed human interaction in automated evolutionary synthesis

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)

3.2. MEMS synthesis quality metric

Design synthesis [12] 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 are dramatically impact the accuracy of the certain 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 [13] 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 [11] we presented a performance metric for these two deficiencies. 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 (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.

In terms of the user study of our new IEC tool. We would like to show that 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.

An analysis of variance (ANOVA) test [14] can be used to measure the level amount of variation between two groups and tell us if it is statistically significant. This test can therefore be applied to compare the two groups of designs for each of the two metrics. If ANOVA tells us there is a significant difference between the two methods, and the improved IEC's results are better, then we can conclude it has a significant performance improvement over the automated tool.

3.3. Results

Using a similar testing strategy employed in [10] and [11], 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 were compared to the results of 10 runs of the automated synthesis program - identical settings and code, except no human interaction is used.

Table 2. Comparison of results of improved IEC user test and automated EC for 4-objective MEMS resonator test problem.

	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)	

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 interaction 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 worse 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 GUI window).

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, this is 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 require 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. Further testing is necessary before any definite conclusions can be drawn.

4. Conclusions / Future Work

This work presents an initial trial of this 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.

But more testing would need to be performed to directly compare the performance of this new IEC to the previous IEC implementation; 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 also like to 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 would like to try to apply this method to the design of other MEMS devices, such as MEMS inertial sensors. Additionally it can be applied to the device or layout design in other engineering domains as well, such as the design of circuits, building structures, HVAC, etc.

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.

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