Optimized Design of MEMS by Evolutionary Multi-objective Optimization with Interactive Evolutionary Computation

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Abstract. We combine interactive evolutionary computation (IEC) with existing evolutionary synthesis software for the design of micromachined resonators and evaluate its effectiveness using human evaluation of the final designs and a test for statistical significance of the improvements. The addition of IEC produces superior designs with fewer potential design or manufacturing problems than those produced through the evolutionary synthesis software alone as it takes advantage of the human ability to perceive design flaws that cannot currently be simulated. A user study has been performed to compare the effectiveness of the IEC enhanced software with the non-interactive software. The results show that the IEC-enhanced synthesis software creates a statistically significant greater number of designs rated *best* by users.

1 Introduction

Microelectrical Mechanical Systems (MEMS) is an emerging field of research with application in a wide variety of areas such as Radio Frequency (RF) communications, optical networking, and environmental monitoring. Current computer-aided design tools for MEMS design are rudimentary and much of current design is based on engineering experience and *back of the envelope* calculations. We have developed automated synthesis tools that allow for the creation of complex devices with desired performance, optimized for a number of design constraints and competing performance goals [3,8,9]. Other notable research in using evolutionary approaches in the MEMS field includes the work of Li [4] and Ma [5]. This work differs from ours in that the focus is on mask layout, fabrication and parametric modeling – but not design synthesis. At a higher level, Fan has worked on using system-level synthesis of RF bandpass filters made up of MEMS components using genetic programming techniques on bond graphs [2].

One of the limitations of our current evolutionary multi-objective optimization (EMO) approach is that it depends on simulation software to evaluate design quality. Unfortunately, there are many design issues that cannot be currently detected by the simulation software. These issues lead to either poor performance

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or premature failure. While many of these potential problems are clearly visible to a human user they would be extremely difficult, if not impossible, to mathematically model and simulate.

We propose to combine the EMO approach with interactive evolutionary computation (IEC) techniques to embed the human user's visual inspection and domain knowledge into the computer-aided MEMS design process. IEC uses evolutionary optimization to evolve a group of designs similar to EMO, but instead relies on a human user to rate each design based on his or her subjective evaluation for performance and shape. This allows the human's judgment and preferences to further shape which designs are developed, avoiding potential design flaws that are hard to model analytically.

2 MEMS Synthesis

The design example chosen for synthesis is a simple surface micro-machined resonating mass. This mass is suspended above the substrate by four legs, comprised of several beam segments. The center mass has two electrostatic "comb drives" attached to it in order to facilitate actuation and capacitive position sensing during characterization. Currently the center mass and comb drive geometry are fixed, only the contents of the four legs are variable. Each leg is comprised by a variable number of beams, and each beam has its own length, width, and angle as free variables (see Fig. 1).

Four objective functions are formulated as a minimization of the distances to four goals: resonant frequency (100 kHz), suspension stiffness in the lateral direction (100 N/m), stiffness in longitudinal direction (1 N/m), and device area (device area goal = 0, i.e. area is minimized). The device area is defined by the area contained within a rectangle bounding the resonator's center mass, comb drives and beams, but not the anchors and contact pads.

Table 1. Design parameters/constraints used for MEMS resonator synthesis comparison.

Parameter Name	Value
Center mass	5.3066e-011 kg
Leg symmetry constraint	On
Manhattan angle only constraint	Off
Max number of beams per leg	7
Min number of beams per leg	1
Max beam length	$100\mu m$
Min beam length	$10\mu m$
Max beam width	$10\mu m$
Min beam width	$2\mu m$
Max beam angle	$\pi/2$
Min beam angle	$-\pi/2$

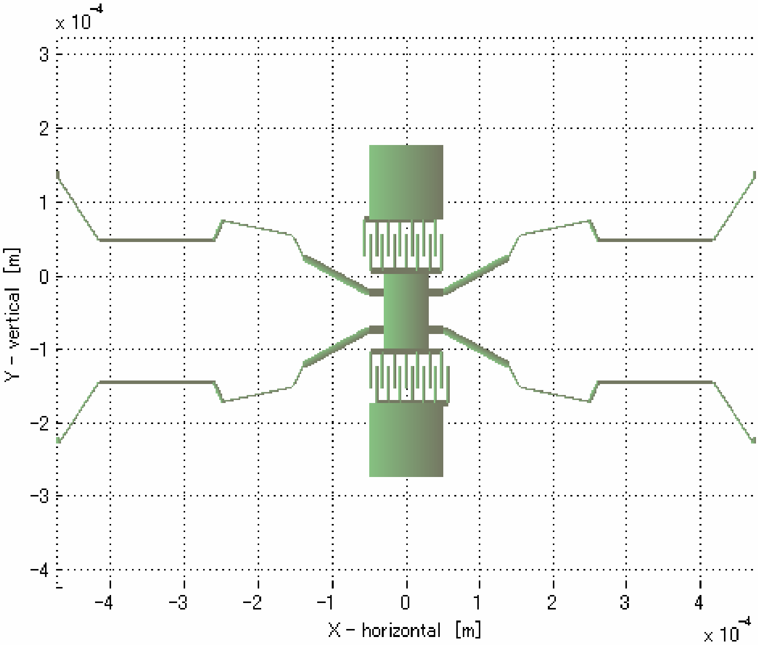

Fig. 1. Example of a MEMS resonator synthesized with EMO software, with symmetric leg constraint applied.

Each beam variable has a set of inequality constraints (max/min length, width and angle), and there is a limit on the number of beams per leg (see Table 1). The center mass is considered a parameter and not a design variable for this research. Basic geometrical checking is performed to prevent beams from crossing each other as such designs could not be fabricated or operated. Furthermore, different symmetry and angle constraints are considered, such as symmetric legs or Manhattan angle constraints. For this research, we limit ourselves to symmetric legs only.

3 Evolutionary Optimization for MEMS

3.1 Evolutionary Multi-objective Optimization

We use a multi-objective genetic algorithm (MOGA) as our EMO approach to developing a population of optimal solutions (see Fig. 2). Given a higher-level description of the device's desired behavior, an initial population of candidate designs is generated randomly from a number of available components such as anchors, beams, electrostatic gaps, and combs. Each design is checked for basic geometrical validity, and our MEMS simulation tool, SUGAR developed at UC

Berkeley [1], evaluates its performance for the multiple objectives: area, resonant frequency, and stiffness. The MOGA is then applied to the initial population to iteratively search for functional designs by applying the genetic operations of selection with elitism, crossover, and mutation to create the next generation of designs. This process continues until an optimal set of Pareto optimal solutions is synthesized.

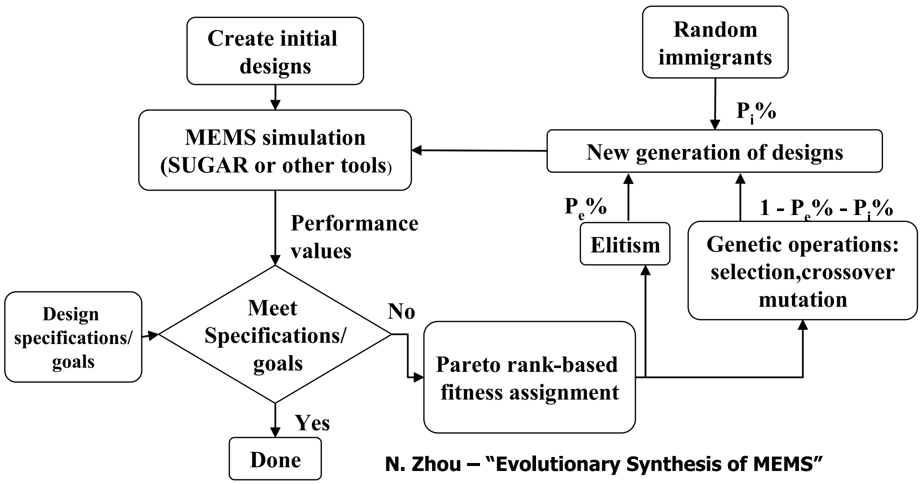

Fig. 2. Evolutionary synthesis.

In order to compare an EMO-only approach to the EMO+IEC approach, we first solve the MEMS resonator example with four objectives using a MOGA implementation with an initial population size of 400, and using the genetic operators of cross-over and mutation. A non-dominated or Pareto set of approximately 60-100 designs is achieved after 30 generations for this example.

Although these designs are Pareto optimal in the solution space according to the objective performance as simulated in SUGAR, they may contain flaws that prevent them from being suitable designs for fabrication. These flaws include potential stress concentrations, *near misses* where two legs come very close to each other without actually crossing in the static case, but may collide while the structure is being resonated, as well as other flaws or features that a human engineer may reject based on previous experience or their engineering knowledge. Of the 60-80 designs in a typical Pareto set returned by the EMO, only 25-30 are within 50% of our most critical objective - resonant frequency. Of these, only approximately four or five designs are free of non-simulated design flaws.

The current simulation software has no means to simulate stress concentrations, transient responses of structures, and other features that a designer might perceive as *awkward* or difficult to fabricate or use. Therefore alternative means of evaluating a design must be sought.

3.2 Interactive Evolutionary Computation (IEC)

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 [7].

The IEC implementation used for this research is a single objective genetic algorithm, similar in structure to the MOGA, except instead of using a simulation tool to gauge the performance of a particular design for multiple objectives, the design is given a single integrated preference score by an IEC human user, and this score is used as the sole objective for ranking design individuals by fitness. In this case, IEC is used to measure the human user's satisfaction with a particular design based on its shape and simulator performance. This allows human knowledge and expertise to be embedded into the synthesis process.

3.3 Integration

Human fatigue is one of the difficulties faced in implementing an IEC approach [7]. Human interaction is required for every evaluation, thus limiting the population size and number of generations that can be used. The current EMO requires on the order of 12,000 evaluations (a population size of 400 over 30 generations) to evolve a group of good solutions from randomly generated initial design individuals. This magnitude of evaluation is not feasible for human interaction, therefore randomly generated starting points for IEC is not practical.

One solution to this problem is to combine the non-interactive EMO and IEC together to use the best attributes of each: the tireless, rapid synthesis of EMO with the ability of IEC to overcome many design flaws and embed human knowledge. The method of combining EMO and IEC chosen was serial; EMO is run, and the individuals of its final evolutionary generation are then used by IEC as an initial population for further interactive evolution. This integration of EMO and IEC is illustrated in Fig. 3.

As the population produced by the EMO process is much larger than that of IEC, a manual data selection step between the two components is added. This allows the human user to select only the designs that are contained within a hyper-rectangle in the objective space (see Fig. 4). Although we use a hyper-rectangle in our experiment, the integrated EMO+IEC concept need not restrict the shape of data selection area.

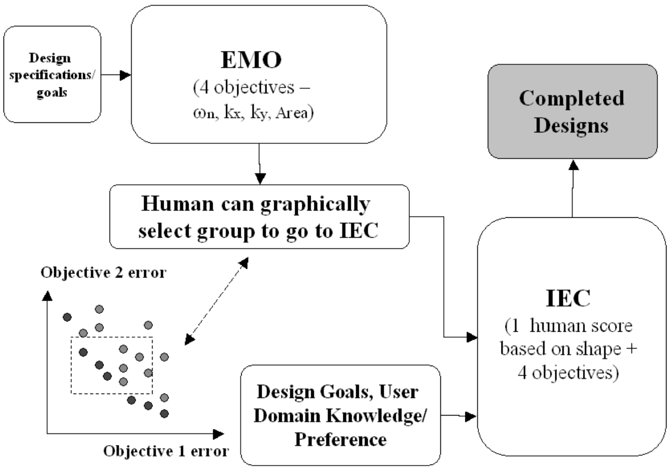

Fig. 3. Integration of EMO system and IEC system in our experiment.

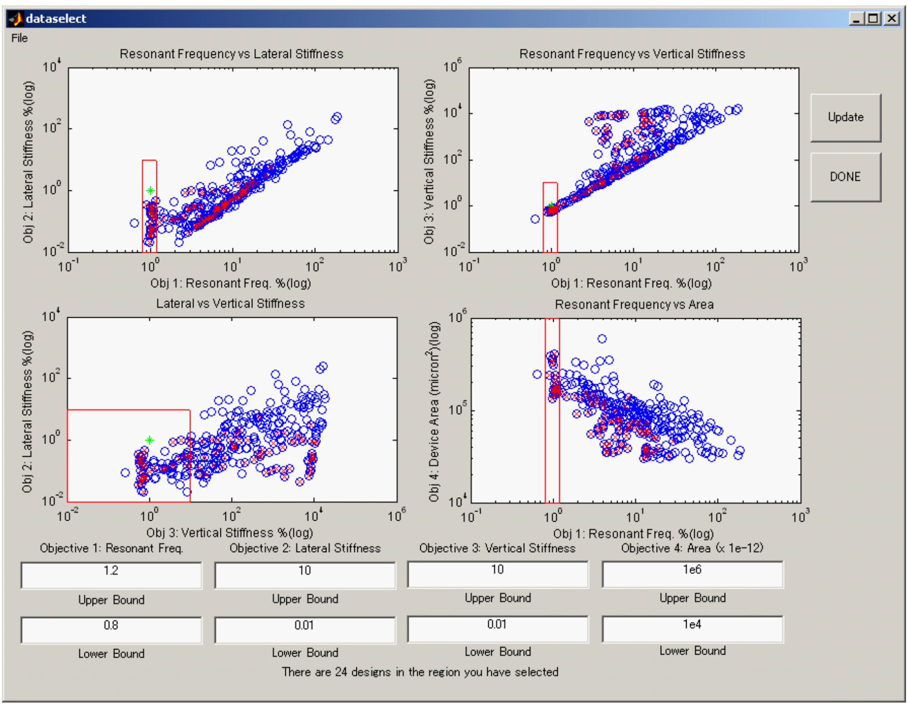

Fig. 4. Data Selection interface to select initial population for IEC.

This step serves to cull the initial population for IEC from a wide array of designs spread around the objective space down to a smaller number of high ranking designs centered around the objective goals. For example, there is little value in further evolving a design that has a resonant frequency that is an order of magnitude or more away from our goal resonant frequency.

Once a region of the EMO solution space is selected, the design candidates contained within it are passed on to the IEC component. These designs serve as a pool from which the initial population is drawn as well as new immigrants in later IEC generations.

For the MEMS resonator example, the IEC interface presents the user with nine designs at a time; each design is graphically displayed, and its performance simulated by SUGAR is presented as a percentage of the goal for each of the four objectives (Fig. 5). The users select a preference score from '*1*' (worst) to '*5*' (best) based on their impression of the shape and performance numbers. As a larger population size will give better, more diverse results, the IEC population size can be set to more than nine. For this paper, a population size of twenty-seven was used; therefore three windows of nine designs each were presented to the user for each evolutional generation.

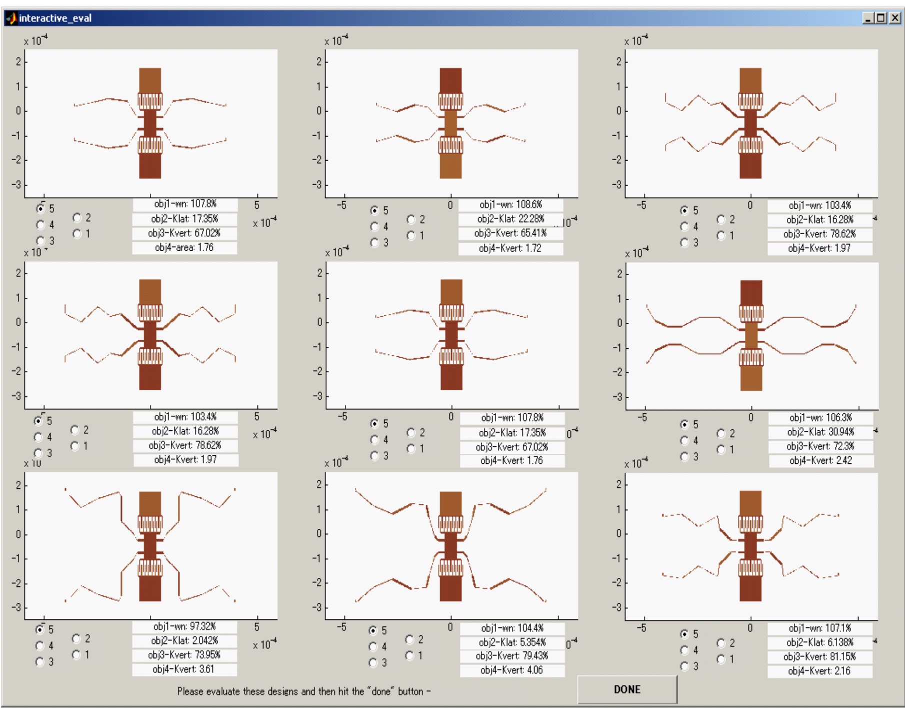

Fig. 5. Rating window for IEC; user gives preference score to nine designs at a time based on shape and performance.

At the completion of each generation's evaluation, the user preference scores are used by the EMO to evolve the next generation. This process continues until the user chooses to end the evolution process.

4 Experimental Evaluation

4.1 Experimental Setup

To gauge the effectiveness of the EMO+IEC implementation, a blind evaluation test for EMO+IEC vs. EMO-alone was performed. First, the MEMS design with EMO-only was conducted, and then IEC applied to the EMO output, using the proposed approach. Designs obtained by both approaches were visually evaluated based on users' domain knowledge. Statistical tests were applied to the difference of evaluation to both approaches.

Users started with an identical population of 400 resonators with symmetric legs generated with EMO. They selected a region to serve as the IEC initial population and scored designs for several generations. Users continued until either satisfied with the results or until the 10th generation was reached.

As a rule of thumb, IEC users were instructed to focus their preference scoring on the resonant frequency, the primary objective of the resonator design, and modify that score up or down based on the performance of the other objectives as well as the user's subjective evaluation of the design shape based on their domain knowledge.

A subjective test for comparison by the same user was conducted after each IEC test was completed. The population of the final generation of EMO+IEC designs was compared side by side to the EMO-only final Pareto set, using the same interface as the IEC window. The EMO+IEC and EMO-only designs were interspersed to ensure unbiased and consistent scoring between the two sets of designs. The users were not informed as to which approach produced any of the designs being evaluated.

Due to the large size of the Pareto design sets – 60 to 80 returned by the EMO-only step in the process for the 4 objectives – only a subset was shown to the user for scoring in this final subjective comparison with EMO+IEC. This subset was generated by taking only the members of the Pareto set within 50% of the resonant frequency goal, reducing the number from 60-80 down to a more manageable 25-35. This step removes the irrelevant designs, only requiring a human score on potentially good designs. This step can be justified because no user will give a resonator design significantly deviating from the primary objective goal a '*5*' score, and it saves the human user the tedium of scoring dozens of poor performing designs; recall that the Pareto set contains designs that are optimal in one or more objective, but could perform very poorly in the other objectives.

The scores given to each approach were tallied and compared. The number of '*5*' scores given by the users for each approach was chosen as the primary metric for effectiveness as we believed that the number of highly ranked feasible designs best measures the ability of the EMO+IEC system to further hone designs developed by the EMO and in incorporate design issues that are difficult, if not impossible, to be numerically optimized.

The degree of MEMS experience in the background of the users was also recorded. Although one might argue that experts with MEMS design experience are better suited to rate MEMS design candidates than non-experts, we note that many of the potential design flaws identified can be observed by basic human visual recognition without necessarily requiring extensive training and experience in the specific field of MEMS. Thus this raises the question of whether non-experts might be trained to recognize good and bad resonator features and perform comparably to experienced MEMS designers in this process.

4.2 Experimental Results

Subjective tests and comparisons were performed on eleven engineering graduate students from the University of California at Berkeley. The number of the best scores, '*5*', given to the designs in the Pareto set of the final generation of the EMO-only and the EMO+IEC tests are presented in Table 2. Here, '+1', '0', and '−1' in the sign column mean that the number of *5*'s in the EMO+IEC Pareto set is more, equivalent, or less than that of EMO-only, respectively.

Table 2. Test results for the user evaluations of MEMS designs with EMO-only and IEC+EMO.

User	Expert?	IEC+EMO: # of *5*'s	EMO: # of *5*'s	sign
1	Y	7	9	−1
2	Y	12	6	1
3	Y	7	3	1
4	N	6	2	1
5	Y	4	4	0
6	Y	11	9	1
7	N	8	7	1
8	Y	1	0	1
9	N	6	3	1
10	N	12	7	1
11	N	9	2	1

An evaluation of the results in Table 2 shows that the EMO+IEC is significantly better than the EMO-only using both the *sign* test [6] ($p < 0.02$), and the *Wilcoxon Matched-Pairs Signed-Ranks* test [6] ($p < 0.01$).

Fig. 6(a) shows an example of a design in the Pareto set returned by the EMO that was given a low score of '*1*' by one of the users. In this case, the user penalized the presence of a sharp corner in the meandering springs due to the potential of the associated stress concentration to lead to premature stress failure. Fig. 6(b) shows an example design generated by the same user with EMO+IEC in which performance numbers predicted by the simulator software are similar, but the user's interaction has produced a design without potential operational flaws.

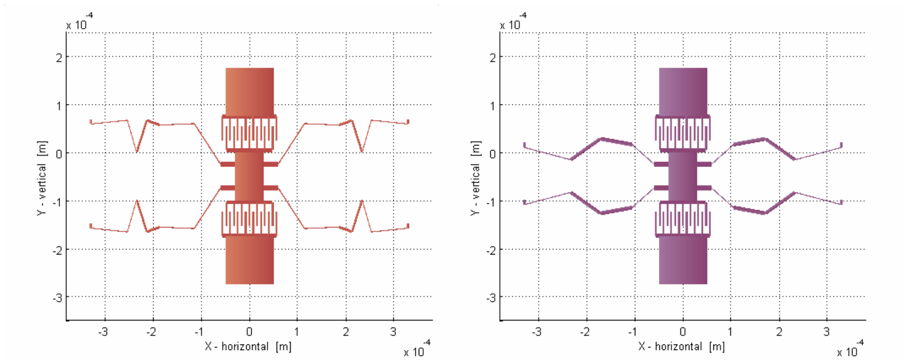

Fig. 6. (a) Left: MEMS resonator design produced by EMO-only, given a low score by a user due to potential stress concentrations in the legs. (b) Right: High scoring EMO+IEC design generated by the same user.

Unfortunately, with only six experts participating, we were not able to draw any statistically relevant conclusions about whether MEMS expertise has any impact on the success of the EMO+IEC framework. As we refine our work in future experiments, we hope to involve more MEMS experts in the testing.

5 Conclusions and Future Work

The impact of human interaction with the synthesis process has yielded some interesting results. We observed that humans tended to give low scores to designs that had particular features the user deemed undesirable. Over the course of several generation this caused families of related designs having those features to die off, thus blocking a road of evolution that the user believes is not worth pursuing. In our IEC test, with only a small population of twenty-seven this led to a rather homogenous population at the end of the evolution process, with most designs receiving a '*5*' score being variations on two or three dominant shapes. This phenomenon could be used as a variant to the EMO+IEC approach, where the human's role is focused explicitly on *killing off* unpromising design concepts.

We have fabricated MEMS resonator designs created with the EMO+IEC and EMO-only software to support these results. Devices were created in the MUMPS process and are currently being tested at the Berkeley Sensors and Actuator Sensor. A scanning electron micrograph of a design produced by an EMO+IEC process is shown in Fig. 7. The performance of these devices will be used to improve our evolutionary synthesis approach as well as the performance of the SUGAR MEMS simulation software. The performance differences between the EMO and EMO+IEC generated devices can be used to further validate the results of the user study presented in this paper.

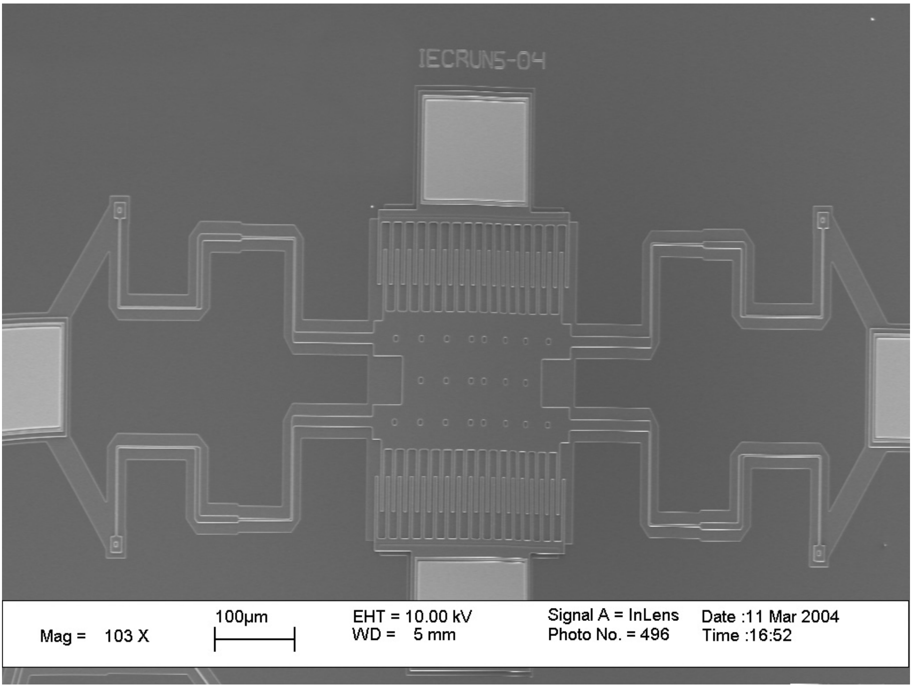

Fig. 7. SEM micrograph of symmetric MEMS resonators created with EMO+IEC.

The results of user testing on the MEMS resonator synthesis example show that using IEC to further evolve designs generated by EMO can produce better results than those using EMO alone. Use of EMO alone does not include critical factors that are difficult, if not impossible, to simulate. As these factors can have a major impact on the effectiveness of a design when fabricated, IEC is able to outperform by incorporating human domain knowledge to produce top ranking designs that are more suitable to the user's judgment of well performing designs.

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