A NOVEL HYBRID GENETIC ALGORITHM AND ITS APPLICATION TO INVERSE PROBLEMS IN MEMS

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Abstract -- A novel hybrid genetic algorithm is proposed in this paper for solving inverse problems in MEMS. The new algorithm presents two hybridization operations in order to speed up the convergence process. It takes only 4.1% ~ 4.7% number of function evaluations required by the conventional genetic algorithm to reach global optima for the benchmark functions tested. The new algorithm is then used for solving two inverse problems. One is the identification of flow-pressure characteristic parameters of the valve-less micropumps. The other is the identification of material property parameters and bonding quality of the piezoelectric patches. Numerical simulations have shown the very satisfactory results.

Keywords: Genetic algorithm; Inverse problems; MEMS

INTRODUCTION

Hybrid genetic algorithms (GAs) have been known as the effective optimization technique for solving the complicated optimization problems [1-3]. As the hybrid algorithms combine the globe explorative power of conventional GAs with the local exploitation behaviors of deterministic optimization methods, they usually outperform the conventional GAs or deterministic optimization methods to be individually used in engineering practice.

In this study, a new hybrid genetic algorithm (called nhGA) is proposed. It presents two hybridization operations. The first one is to use a simple interpolation method to move the best individual produced by the conventional genetic operations to an even better neighboring point in each of generations. The second one is to use a hill-climbing search to move a randomly selected individual to its local optimum. This is may be done only when the first hybrid operation fails to improve the best individual consecutively in several generations. Compared with the other hybrid GAs, the nhGA is not only excellent in the convergence performance, but also very simple and easy to be implemented in engineering practice.

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As an effective optimization method, the nhGA is used for solving two inverse problems in MEMS. The first one is to identify the dynamic flow-pressure characteristic parameters of the valve-less micropumps. The second one is to identify the material property parameters and bonding quality of the piezoelectric patches. Both of them have demonstrated the excellent performance of the nhGA for inverse problems.

HYBRID GENETIC ALGORITHM (nhGA)

Algorithm Description

Basically, the nhGA proposed in this study is the further development for the hybrid GA called hGA [4]. As the hGA has been discussed in detail in Ref. [4], which may be used as a reference to explain the mechanism of nhGA, it is decided herein to only give a brief description for the implementation process of nhGA as follows:

(1) j=0, start up the evolutionary process.
  - (a) Select the operation parameters including population size N, crossover possibility p_c, mutation possibility p_m, random seed i_d, control parameter α and β [4], etc.
  - (b) Initialize N individuals, $P(j)=(p_{j1}, p_{j2},\ldots,p_{jN})$, using a random method. Every individual p_{ji} (i=1,…,N) is a candidate solution.
  - (c) Evaluate the fitness values of $P(j)$.

(2) Check the termination condition. If "yes", the evolutionary process ends. Otherwise, j=j+1 and proceed to next step.

(3) Carry out the conventional genetic operations in order to generate the offspring, i.e. the next generation of solutions, $C(j)=(c_{j1}, c_{j2},\ldots,c_{jN})$.

These operations to be used include niching [5], selection [1], crossover [1], elitism [5], etc.

(4) Implement the first hybridization operation.

(a) Construct the move direction $\bar{d}$ of best individual.

$$\bar{d} = (c_j^b - c) \quad (1)$$

$$c = \begin{cases} c_{j-1}^b & c_j^b \neq c_{j-1}^b \\ c_j^s & c_j^b = c_{j-1}^b \end{cases} \quad (2)$$

Where c_{j-1}^b is the best individual in $C(j\text{-}1)$ at the j-1-th generation, c_j^b and c_j^s are the best and second best individuals in $C(j)$ at the j-th generation, respectively.

(b) Generate two new individuals c_1, c_2, and evaluate their fitness values.

$$c_1 = c_j^b + \alpha \bar{d} \quad (3)$$

$$c_2 = c_{j-1}^b + \beta \bar{d} \quad (4)$$

where α and β are control parameters. They are recommended to be within 0.1 ~ 05 and 0.3 ~ 0.7, respectively.

(c) Select a better individual c_m,

$$f(c_m) = \max\{f(c_1), f(c_2)\} \qquad c_m \in \{c_1, c_2\} \quad (5)$$

$f(.)$ is the fitness function.

(d) Replace the individual c_j^b in $C(j)$ with the individual c_m. This results in a upgraded offspring $C_u(j)=(c_{j1}, c_{j2},\ldots,c_m,\ldots,c_{jN-1})$.

(e) Check if there occurs population convergence in $C_u(j)$. If "yes", implement restarting strategy [4] to generate the new $C(j)$.

(5) Check if the best individual keeps unimproved consecutively in the M generations (M=3~5). If "yes', implement the second hybrid operation as follows.

(a) Randomly select a individual c_{ji} in $C_u(j)$.

(b) Take c_{ji} as an initial point to start the hill-climbing search.

(c) Replace individual c_{ji} with the local optimum c_{jL} obtained by the hill-climbing search.

(6) Go back to step (2).

It is clear from the above description that the newly proposed nhGA, compared with the previous hGA, does not incur any deterioration of population diversity when incorporated with the hybridization operations.

Performance Tests

Three benchmark functions are used to test the nhGA. Each of benchmark functions has lots of local optima and one or more global optima. Figure 1 shows the search space of function *F1*.

F1: $$f(x_1, x_2) = \prod_{i=1}^{2} \sin(5.1\pi x_i + 0.5)^{80} e^{-4\log 2(x_i - 0.0667)^2/0.64}$$

π=3.14159, $0 < x_i < 1.0$, i=1,2

F2:

$$f(x_1, x_2, x_3) = \sum_{i=1}^{10} \{e^{-ix_1/10} - e^{-ix_2/10} - [e^{-i/10} - e^{-i}]x_3\}^2$$

$-5 < x_i < 15$, i=1,2,3

F3: $$f(x_1,\ldots,x_5) = \pi\{10\sin(\pi x_1)^2 + \sum_{i=1}^{4}[(x_i - 1)^2(1 + 10\sin(\pi x_{i+1})^2]\}/5 + (x_5 - 1)^2$$

π=3.14159, $-10 < x_i < 10$, i=1,…,5

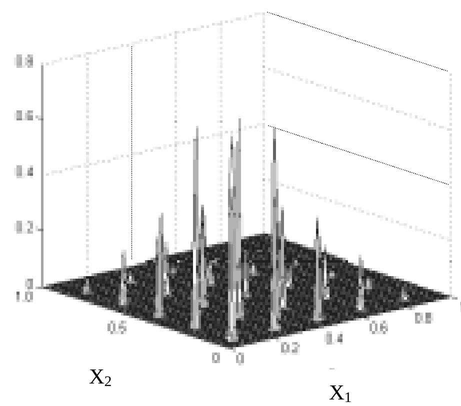

Fig. 1. Search space of benchmark function F1.

For each of benchmark functions, the nhGA runs 10 times with the different random seed i_d. The 10 random seeds are -1×10^2, -5×10^2, -1×10^4, -1.5×10^4, -2×10^4, -3×10^4, -3.5×10^4, -4×10^4, -4.5×10^4, -5×10^4, respectively. The other operation parameters are N=5, p_c=0.5, p_m=0.02, α=0.2, β = 0.5 and M=3. Tournament selection, one child, niching, elitism are chosen to use. Table 1 shows the mean numbers of function evaluations, $\bar{n}$ and $\bar{n}_m$, that are taken to reach the global optima using the nhGA and conventional mGA [5], respectively. It can be found that the nhGA demonstrates a much faster convergence than the conventional mGA.

Table 1
Mean numbers of function evaluations to convergence

No.	Global	Func.	$\bar{n}$	$\bar{n}_m$	$\bar{n}/\bar{n}_m$

	Optimum	Value			(%)
F1	(0.0669, 0.0669)	1.0	141	3365	4.2
F2	(1, 10, 1)	0.0	237	5745	4.1
F3	(1, 1, 1, 1, 1, 1)	0.0	6637	139915	4.7

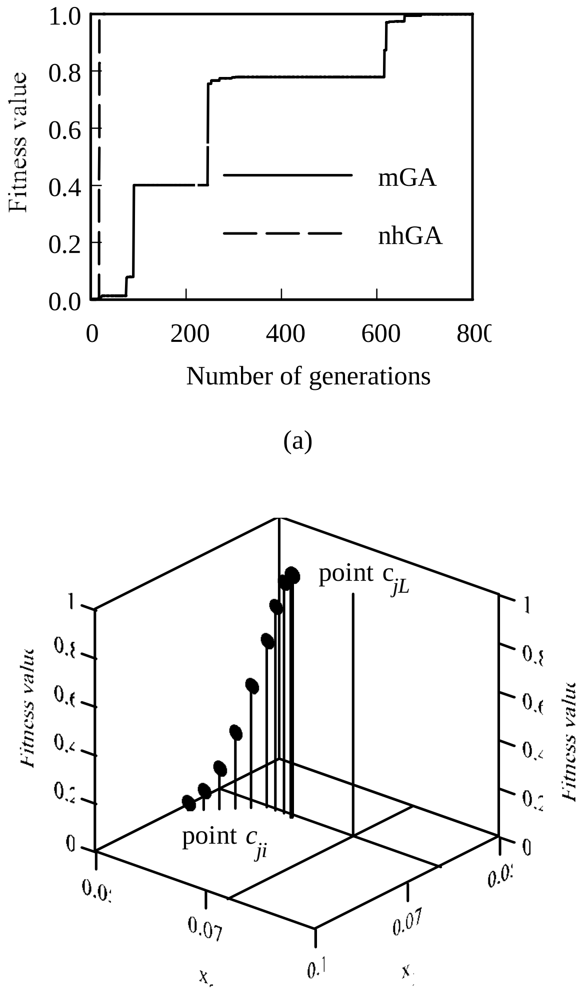

Fig. 2. (a) Convergence process in view of generations. (b) Hill-climbing process in hybridization operation.

Figure 2 shows the convergence processes of benchmark function *F1* when using the nhGA against the mGA, from which comparison of the convergence processes between nhGA and mGA can be seen more clearly.

INVERSE PROBLEM SOLVING

Parameter Identification of the Valve-less Micropumps

Figure 3 schematically shows a valve-less micropump. The pressure-loss coefficients, ζ_p and ζ_n, in the flow channels can be optimally solved from the following objective function [6]:

$$\min E(\zeta_p, \zeta_n) = \left(\sum_{i=1}^{n} \left| Q_i(\zeta_p, \zeta_n) - Q_i^m \right|^2\right)^{\frac{1}{2}} \quad (6)$$

$$i=1,\ldots, K, \ \zeta_{pmax} \le \zeta_p \le \zeta_{pmin}, \ \zeta_{nmax} \le \zeta_n \le \zeta_{nmin}$$

$Q_i(\zeta_p, \zeta_n)$ is the mean flux calculated from a complicated model [5] using the trial ζ_p and ζ_n, Q_m^i is the measured mean flux at the *i*-th trial. *K* is the number of trials.

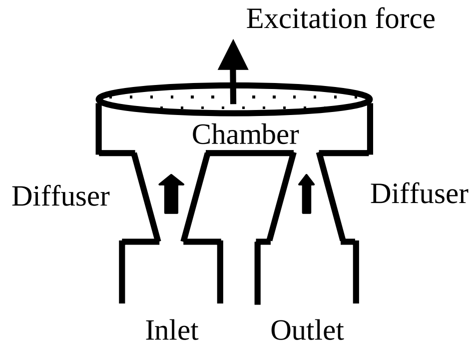

Fig. 3. Cross-sectional view of a micropump.

Table 2
Solutions for 3 simulated cases

	n	ζ_p	ζ_n	$e(\zeta_p)$ (%)	$e(\zeta_n)$ (%)
Case I	790	1.389	0.918	-4.9	-3.4
Case II	767	1.307	0.894	2.1	2.8
Case III	525	1.112	0.443	5.9	5.5

The nhGA is used for solving this problem. Table 2 shows the corresponding solutions for 3 simulated cases. In Table 2, *n* is the number of function evaluations taken by the nhGA, ζ_p and ζ_n are the solved pressure-loss coefficients, $e(\zeta_p)$ and $e(\zeta_n)$ are the errors with respect to their true values, respectively. It can be seen that nhGA converges to the satisfactory results very fast. The maximal error of solved ζ_p and ζ_n are only -4.9%, 2.8% and 5.9% for 3 simulated cases, respectively.

Property Parameter and Bonding Equality Identification of the Piezoelectric Patches

Piezoelectric (PZT) patches have been widely used as actuators and sensors in MEMS. Their property parameters and bonding equalities are usually required to calibrate in order to obtain the accurate analysis results [7]. As usually done, an optimization problem is formed as follows to this end.

$$\min MSF = \sum_{i=1}^{N} \left[\mathrm{Re}(Y_i) - \mathrm{Re}(Y_{mi})\right]^2 \qquad (7)$$

Where

$$Y = j\omega a(\varepsilon_{11}^{\sigma} - d_{31}^2 E_{11}^E + \frac{d_{31}^2 E_{11}^E Z_a}{Z_a + \xi Z_s} \frac{\tan(kl)}{kl}) \qquad (8)$$

N is the number of frequency sampling, $\mathrm{Re}(Y_i)$ and $\mathrm{Re}(Y_m)$ are the real parts of calculated and measured electric admittance of PZT patch at sampling point i, respectively. ξ is a coefficient representing the equality of bonding layer [7]. Figure 4 shows its effect on the electric admittance for a one-dimension example [7]. In this study, only dielectric constant $\varepsilon_{31}^{\sigma}$, piezoelectric constant d_{31}, elastic modulus E_{11}^E and coefficient ξ are assumed to be varied and need to be identified using the nhGA. The other parameters can be found in Ref. [7].

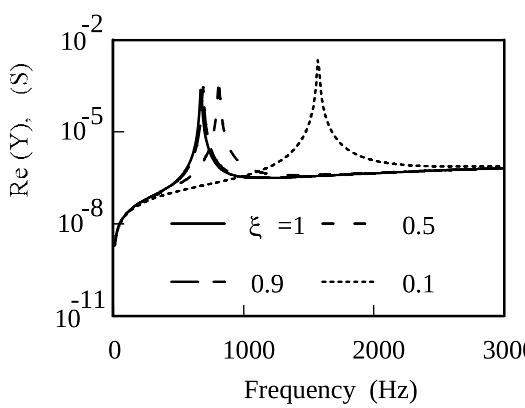

Fig. 4. Effect of coefficient ξ on admittance.

It is set 3 simulated cases where the 4 parameters to be identified are 85%, 100% and 115% of their nominal values, respectively [7]. With the given parameter values in each case, the electric admittance calculated from Eq. (8) is taken as the measured Y_m. Then, these parameters are allowed to vary within the range of from 50% to 150% off from their nominal values. The nhGA is used to find the optimal solution. It is found out that the maximal errors of identified 4 parameters with respect to their specified values are only 4.3%, 3.7% and 4.8%, respectively. The computation costs are also very low. The maximal number of function evaluations required is 873.

CONCLUSIONS

In this study, a novel nhGA is proposed and validated using 3 benchmark functions. It is also used to solve two typical inverse problems in MEMS. Numerical examples have demonstrated its effectiveness and efficiency. This provides a new choice for solving complicated optimization problems as well as inverse problems in engineering practice.

References

1. D. E. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wesley publishing company, USA, 1989.
2. T. Back, U. Hammel and H. P. Schwefel, “Evolutionary computation: comments on the history and current state,” IEEE Trans. Evol. Comput., vol. 1, pp. 3-17, 1997.
3. M. Gen and R. W. Chen, Genetic Algorithms and Engineering Design, John Wiley & Sons, New York, 1997.
4. Y. G. Xu, G. R. Liu and Z. P. Wu, “A novel hybrid genetic algorithm using local optimizer based on heuristic pattern move,” Appl. Artif. Intell. – An Int. J. vol. 15, pp. 601-631, 2001.
5. D. L. Carroll, “Genetic algorithms and optimizing chemical oxygen-iodine lasers,” Developments in Theor. and Appl. Mech. Uni. of Alabama, vol. 10, pp. 411-424, 1996.
6. Y. G. Xu, G. R. Liu, L. S. Pan and N. Y. Ng, “Parameter Identification of Dynamic Flow-Pressure Characteristics in Valve-less Micropumps,” *J. of Micromech. Microeng.*, Submitted for publication, July 2001.
7. Y. G. Xu and G. R. Liu, “A Modified Electro-Mechanical Impedance Model of Piezoelectric Actuator-Sensor for Debonding Detection of Composite Repair Patch,” *J. of Intelli. Materi. Sys. Struc.*, Submitted for publication, Nov. 2001.