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USE OF THE STEADY-STATE GENETIC ALGORITHM FOR FINDING OPTIMAL CALIBRATION POINTS OF SMART SENSORS

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Abstract

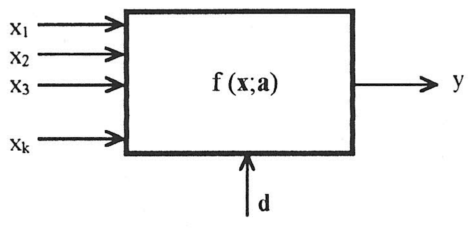
A concept of application a genetic algorithm (GA) to finding the best position of calibrating points under random conditions is presented in the paper. Steady-state GA skeleton and genetic operators are described. Comparison of the results of experiments for the genetic and a Monte-Carlo (M-C) algorithm applied to the calibration of differential pressure sensor is provided.

1. Introduction

Recently, a lot of attention has been paid to the problem of optimal calibration of smart sensors [3]. It is a very important problem during manufacturing because the price of smart sensors is strongly dependent on calibration time. Most of nonelectrical quantities are difficult to set up fast and accurately (for instance temperature, gas mixture, humidity, etc...). Therefore calibration process is time consuming. Thus an efficient extraction of model parameters is needed. At its simplest, optimal calibration can be stated as the problem of achievement of maximal accuracy with minimal number of measurements [1] [2].

1.1 Problem Description

Scheme of smart sensor with multiparameter method applied may be shown as follows:



Output value y is a function of vector **x** and random disturbance **d** which is inherent in measurement process. Vector **d** represents also inaccuracy of standards used in calibration process.

$$y = \overset{o}{f}(\mathbf{x}) + \mathbf{d}$$

During the calibration the set of model parameters **a** should be found.

$$\hat{y} = f(\mathbf{x}\,;\mathbf{a})$$

In practice, linear models (linear combination of basis functions) and Least Square Method (LSM) for calculating parameters **a** are used.

$$\hat{y} = [\mathbf{b}(\mathbf{x})]^{\mathrm{T}} \mathbf{a}$$

The most often suitable combination of polynomials is applied

$$\mathbf{b}(\mathbf{x}) = [1,\ x_1,\ x_2,\ \ldots,\ x_k,\ x_1x_2,\ x_2x_3,\ \ldots,\ x_kx_1,\ x_1^2,\ x_2^2,\ \ldots,\ x_k^2,\ x_1x_2^2,\ \ldots,\ x_1^3,\ \ldots,\ x_k^3, \ldots]^T$$

Using calibration data:

$$\{x_1(n), x_2(n), \ldots, x_k(n), y(n)\} \quad n = 1,2,\ldots,N \ ,$$

planning matrix **B**

$$\mathbf{B} = \begin{bmatrix} \mathbf{b}(\mathbf{x})^{\mathrm{T}}(1) \\ \mathbf{b}(\mathbf{x})^{\mathrm{T}}(2) \\ \vdots \\ \mathbf{b}(\mathbf{x})^{\mathrm{T}}(N) \end{bmatrix}$$

and the set **a** of the model parameters can be calculated.

$$\mathbf{a} = (\mathbf{B}^{\mathrm{T}}\mathbf{B})^{-1}\mathbf{B}^{\mathrm{T}}\mathbf{y}$$

Many optimal criteria are applied to find the proper position of calibration points. The most important are: [2],[4]

- orthogonal plan, it means that information matrix $\mathbf{B}^{\mathrm{T}}\mathbf{B}$ is diagonal
- rotary plan, it means that estimation of variance prognosis of the model output $\mathbf{x}^{\mathrm{T}}(\mathbf{B}^{\mathrm{T}}\mathbf{B})^{-1}\mathbf{x}\hat{\sigma}^2$ is equal on sphere surface with the centre point placed in the centre of experiment
- D-optimal plan minimises volume of the confidence ellipsoid for each parameter a_i, which is equivalent to the minimisation of $det(\mathbf{B}^{\mathrm{T}}\mathbf{B})$
- E-optimal plan minimises average variance of parameters **a** , which is equivalent to minimisation of $tr(\mathbf{B}^{\mathrm{T}}\mathbf{B})^{-1}$

The criteria described above may by used under fulfilling assumption about independence of disturbances and their normal distribution $\mathbf{d} \in N(0, \sigma^2)$. LSM also does not show any estimation of error between calibration points, so the aim of calibration:

$$\min(\max(\hat{y}(\mathbf{x}) - y(\mathbf{x}))) \quad \forall \mathbf{x} \in [0, FS] \subset \mathbf{R} \tag{1}$$

may not be achieved. [1]

1.2 GA Approach

Genetic approach to solve problem (1) contains a few steps:

1. Choosing representative sensor or set of sensors from fabrication line
2. Precise identification of samples characteristic $y(\mathbf{x})$.
3. Creating numerical model useful for computation. It means that we have a big set of pairs (**x**,y) (with disturbance) and points not measured may by calculated from value of their neighbours.
4. Computing by GA the best calibration point placement with additional constrains for the placement of points and their number.

This approach is free of assumption laid in mathematical theory of optimisation of calibrating points mentioned above and also fulfils min. max. aim of calibration (1).

2. Characterisation of Genetic Algorithm

The finding of optimal calibration points was done using Steady State GA with proportional selection[6]. Some important features of created GA are presented below.

2.1 Encoding

Each solution of the problem is represented by standardised vector of size k+1, where k is equal to multiplied number of calibration points by number of space dimensions of calibrating function. Full population is consisted of the following vectors

$$\{x_1(n), x_2(n), \ldots, x_k(n), \hat{y}(n)\} \quad n = 1,2,\ldots,N_C \quad \forall x \in \langle 0;1 \rangle$$

2.2 Crossover operator

Intermediate crossover operator with averaging in the space was used. Offspring chromosomes C are created from parent chromosomes P according to the formula:

$$x_i^{C_1} = \chi_i \cdot x_i^{P_1} + (1-\chi_i) \cdot x_i^{P_2}$$

$$x_i^{C_2} = \chi_i \cdot x_i^{P_2} + (1-\chi_i) \cdot x_i^{P_1}$$

where χ_i is a random variable uniformly distributed on $\langle 0, 0.05 \rangle$

2.3 Mutation operator

In mutation a new chromosome C is created from parental chromosome P using Gaussian random variables with zero mean and standard deviation equal to 1:

$$x_i^{C_i} = x_i^{P_i} + N(0,1) \cdot \eta$$

where η is parameter from set $\langle 0, 0.2 \rangle$. At the beginning it starts from maximum and finally reaches minimum. Linear decrease was used.

2.4 Fitness function

The objective function of each solution is defined as follows:

$$\xi(\mathbf{x}) = \max_j(\hat{y}_i(\mathbf{x}) - y(\mathbf{x})) \quad \forall \mathbf{x} \in [0, FS] \subset \mathbf{R} \quad i = 1,2,\ldots N_R, \quad j = 12,\ldots N_E,$$

For each vector **x** model parameters are calculated, next the maximum distance between model and output sensor function is searched. This process is repeated N_R times to increase confidence. The fitness function is calculated as :

$$\phi(\mathbf{x}) = \frac{1}{\xi(\mathbf{x})}$$

During the experiments it turned out that it is possible to speed up evaluating the fitness function by limiting number of checking points (used for calculation $\xi(\mathbf{x})$) to N_E without loosing converging ability of GA.

2.5 Implementation of GA

The following steady-state GA procedure was used in experiments.

1. Generate at random an initial population of N_P individuals.
2. Evaluate each individual in the current population according to the cost function
3. Select at random N_C individuals with probability of taking proportional to value of cost function and cross them over replacing the N_C worst ones.
4. Mutate N_M selected at random from the current population
5. If the stop condition is not attained loop to step 2, else stop.

The parameters used were N_P=50, N_C=2, N_M=4.

3. Experimental results

For the experiments, a characteristic of differential capacitive pressure sensor was used. In this case capacitance is proportional to displacement of membrane cased by applied pressure. Actually this formula takes linear form only when displacement is relatively small to diameter of membrane with assumption of constant temperature. To achieve reliable sensor (with wide span and accurate) it is needed to use second or third order polynomial for calculating pressure from capacitance and ambient temperature.

The following basis of functions was applied: $\mathbf{b(x)} = [1,\ x_1,\ x_2,\ x_1x_2,\ x_1^2,\ x_2^2]^T$

Measurement error was taken on level $\delta x = 0.5\%$; $\delta y = 0.1\%$

Calculations were aimed to find the best position of calibrating points where number of calibration points was equal to 6, 7, 8 and 9. The results of this tests are summarised in Table 1

Type of algorithm	Number of calibration points			
	6	7	8	9
Monte-Carlo	3.5%	2.7%	2.3%	2.3%
Genetic	2.4%	2.3%	2.3%	2.2%

Table 1. The average calibration error obtained for the best solution.

Comparison of the best solutions found by GA against M-C method, evidences that the GA gives better points for calibration (especially for the small number of points, witch is of most practical value). It is also important that GA was less time consuming (approximately 8 ÷10 times).

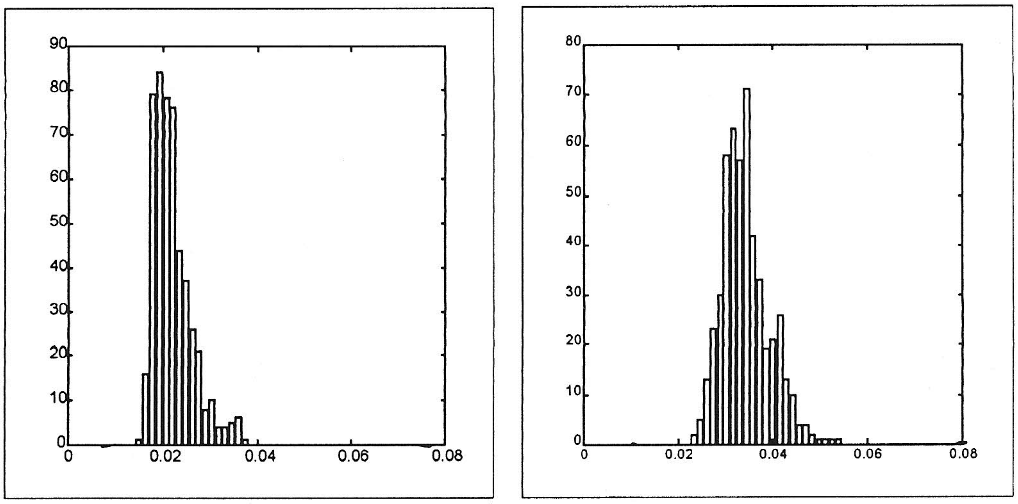


Figure 1. Distribution of maximum calibration error obtained for population of 500 calibrated sensors functions with usage the best calibration points calculated by GA (on the left) and MC (on the right) algorithm

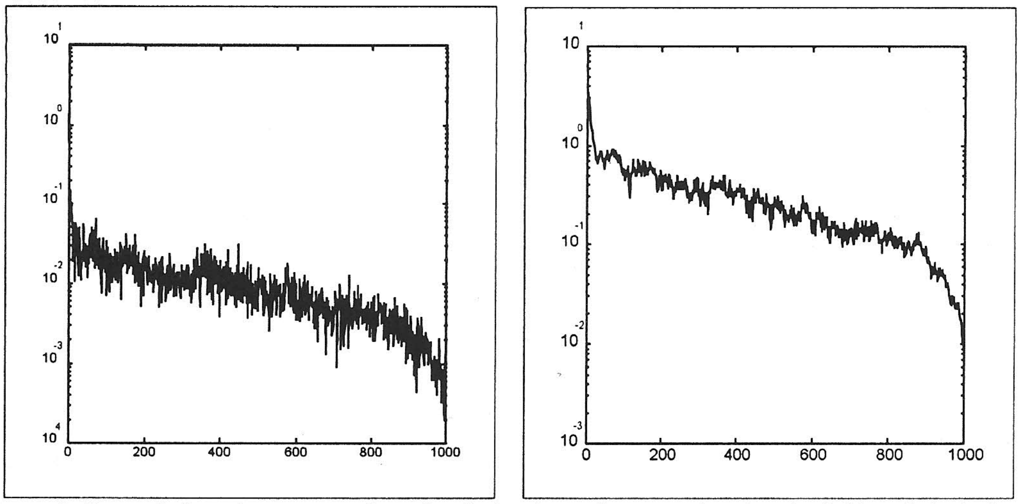


Figure 2. Sum of changing mean value of solution in each generation (on the left) and deviation (on the right) in population versus number of generation GA.

4. Conclusions

Genetic Algorithms shows promise in the area of optimisation calibrating points of smart sensors. Nowadays strict mathematical formulas covering efficient assigning of calibrating points of complex function in random condition are not known, so achieving better results may be possible by using heuristic method.

Plans for future work are concerned to building hybrid genetic algorithm, the different operators and more sophisticated cost function to include case of prediction both number and placement of calibrating points under set restriction.

5. References

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WYZNACZANIE OPTYMALNEGO POŁOŻENIA PUNKTÓW KALIBRACYJNYCH DLA CZUJNIKÓW INTELIGENTNYCH PRZY UŻYCIU ALGORYTMÓW GENETYCZNYCH

Streszczenie

Artykuł prezentuje koncepcję zastosowania algorytmów genetycznych przy wyznaczaniu optymalnych punktów kalibracyjnych w warunkach randomizowanych. Opisano algorytm typu „steady-state" z uwypukleniem poszczególnych operatorów genetycznych. Przedstawiono wyniki testów porównawczych algorytmu genetycznego i algorytmu Monte-Carlo przeprowadzonych na charakterystyce różnicowego czujnika ciśnienia.