Correction of sensor's dynamic error caused by system limitations

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Abstract: The method based on particle swarm optimization (PSO) integrated with functional link articial neural network (FLANN) for correcting dynamic characteristics of sensor is used to reduce sensor's dynamic error caused by its system limitations. Combining the advantages of PSO and FLANN, with this method a dynamic compensator can be realized without knowing the dynamic model of the sensor. According to the input and output of the sensor and the reference model, the weights of the network trained were used to initialize one particle station of the whole particle swarm when the training of the FLANN had been finished. Then PSO algorithm was applied, and the global best particle station of the particle swarm was the parameters of the compensator. The feasibility of dynamic compensation method is tested. Simulation results from simulator of sensor show that the results after being compensated have given a good description to input signals.

Key words: particle swarm optimization (PSO); functional link articial neural network (FLANN); dynamic error; dynamic compensation

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In test system, if the sensor's working frequency bandwidth is narrower than tested signal frequency bandwidth, the spectral components outside working frequency bandwidth will be distorted and the measured results can not describe the tested signal[1,2]. At present, the compensation method is using a dynamic compensator to process the output signal[3]. The method based on FLANN has been used widely, but the FLANN has some problems in different environment such as the local minimum problem, the unwanted study problem and so on[4]. PSO has also been used widely, but its optimized results are easily affected by initial conditions[5]. Combining the advantages and disadvantages of two optimization algorithms, the method based on PSO integrated with FLANN is presented in this paper, the feasibility and the fields of the applications are also discussed.

1 Dynamic compensation of sensors based on PSO integrated with FLANN

The principle of dynamic compensation of sensors is shown in Fig.1.

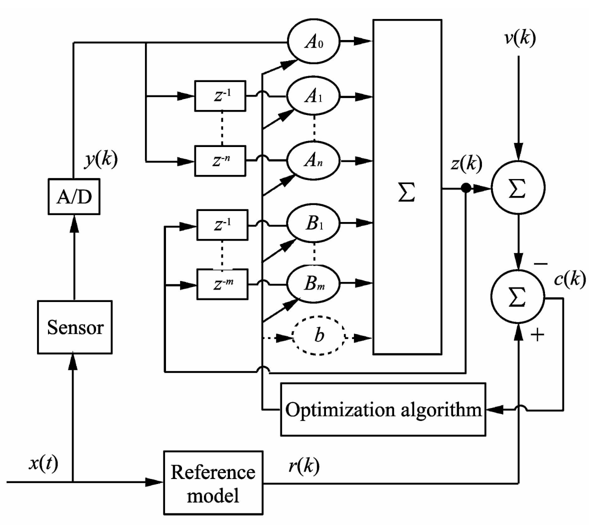

Fig.1 Principle of dynamic compensation of sensors

where $x(t)$ is the dynamic excitation signal, $y(k)$ represents sensor dynamic response signal, $r(k)$ is the expected sensor dynamic response result, $z(k)$ is sensor responses after compensation and $e(k)$ is the dynamic compensation error. The principle of dynamic compensator, therefore, is that the correctional result $z(k)$ after compensation should approach the required ideal responses $r(k)$ as close as

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possible and keep the loss function of the residual error sequence $e(k)$ minimum. According to Fig. 1, $z(k)$ can be expressed as

$$z(k) = (A_0 + A_1 z^{-1} + \cdots + A_n z^{-n}) y(k) - (B_1 z^{-1} + \cdots + B_m z^{-m}) z(k) + g(k), \quad (1)$$

where $g(k)$ denotes a uniformly random noise, m and n are the steps of compensator, $A_0, \cdots, A_n$ and $B_0, \cdots, B_n$ are the coefficients of the compensator.

The vector form of coefficients can be expressed as

$$\boldsymbol{W} = [\boldsymbol{A}, \boldsymbol{B}]^{\mathrm{T}} = [\boldsymbol{A}_1, \cdots, \boldsymbol{A}_n, \boldsymbol{B}_1, \cdots, \boldsymbol{B}_m]^{\mathrm{T}}. \quad (2)$$

The mean square error (MSE) between $z(k)$ and $r(k)$ is

$$J = \frac{1}{N} \times \sum_{k=0}^{N} e(k)^2 = \frac{1}{N} \times \sum_{k=0}^{N} (r(k) - z(k))^2, \quad (3)$$

where N denotes the sampling number.

1.1 Principle of dynamic compensation of sensors based on FLANN

In Fig. 1, if we take FLANN as optimization algorithm, the principle of dynamic compensation of sensors based on FLANN is that the response of compensator $z(k)$ and real ones $y(k)$ of the sensors have been used as the inputs of FLANN. Then by the function link, the inputs $\boldsymbol{X}(k)$ can be expanded as

$$\boldsymbol{X}(k) = [z(k), \cdots, z(k-m), y(k), \cdots, y(k-n)]. \quad (4)$$

The output $z(k)$ will be generated by the neural function through a weighted sum. The vector form of $z(k)$ can be expressed as

$$\boldsymbol{z}(k) = \boldsymbol{W} \cdot \boldsymbol{X}(k) + \boldsymbol{b}, \quad (5)$$

where $k = 1, \cdots, N$, $\boldsymbol{W}$ is the vector form of coefficients, b is a threshold in which considering that network learning is a continuous training and updating process. The weight parameters $\boldsymbol{W}$ and $\boldsymbol{b}$ in Fig. 1 will vary with the training process, therefore, we define

$$\boldsymbol{W}(i) = [\boldsymbol{A}(i), \boldsymbol{B}(i)]^{\mathrm{T}} = [A_1(i), \cdots, A_n(i), B_1(i), \cdots, B_m(i)]^{\mathrm{T}}, \text{ and } \boldsymbol{b}(i), \quad (6)$$

where $\boldsymbol{w}(i)$ and $\boldsymbol{b}(i)$ denote the current values of $\boldsymbol{W}$ and $\boldsymbol{b}$, when FLANN trains to the ith step.

Thus, the output expression of the network is

$$\boldsymbol{z}(k) = \boldsymbol{W}(k-1) \cdot \boldsymbol{X}(k) + \boldsymbol{b}(k-1). \quad (7)$$

In every step, the expression of weight parameter adjustment is

$$\boldsymbol{W}(k+1) = \boldsymbol{W}(k) + \alpha \times \boldsymbol{X}(k+1) \times \boldsymbol{e}(k), \quad (8)$$

$$\boldsymbol{b}(k+1) = \boldsymbol{b}(k) + \alpha \times \boldsymbol{e}(k+1), \quad (9)$$

where α is a learning factor which can control the stability and the rate of convergence.

After a series of training, when the mean square error J is less than the setting value, the current values of the network weight parameters are just the ultimate results[6].

1.2 Principle of dynamic compensation of sensors based on PSO

PSO algorithm is a global optimization method based on SI (swarm intelligence). It searches D-dimensional search space for optimum solution through a population of particles[7]. The particle has two attribute values: speed and position. Position can be expressed by $\boldsymbol{x}_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$, and velocity can be denoted with $\boldsymbol{v}_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$, where $\boldsymbol{x}_i$ represents a potential solution for the problem. The best position of ith particle can be expressed by ***pbest*** $= (p_{i1}, p_{i2}, \cdots, p_{iD})$. The global best position of all the particles can be expressed by ***gbest*** $= (p_{g1}, p_{g2}, \cdots, p_{gD})$. According to the above individual best and global best, the ith particle velocity with respect to the dth dimension is updated by the following equation[8]:

$$v_{id}(n+1) = w v_{id}(n) + c_1 r_{1d}(n)(p_{id} - x_{id}(n)) + c_2 r_{2d}(n)(p_{gd} - x_{id}(n)), \quad (10)$$

where w is called the inertia weight that controls the impact of the current velocity on the next velocity and it is given by a constant; c_1 and c_2 are the positive acceleration coefficients that pull each particle towards the individual best and global best positions; n represents iteration times; r_{1d} and r_{2d} are uniformly random numbers chosen from the interval $[0,1]$[9]. After obtaining the velocity updating formula, each particle moves its corresponding position according to the following updating equation

$$x_{id}(n+1) = x_{id}(n) + v_{id}(n+1). \quad (11)$$

In Fig. 2, if we take PSO as optimization algorithm, in order to obtain an optimal coefficients $\boldsymbol{W}$, the optimization variable $\boldsymbol{W}$ should be coded to become particle of PSO algorithm[10]. According to characteristics of PSO algorithm, parameters can be denoted with real number[11]. If the current position of particle is denoted with $\boldsymbol{W}$ according to Eq. (2), the velocity is denoted with $\boldsymbol{v} = (v_1, v_2, \cdots, v_{n+m})$, and fitness function which confirms the superiorityinferiority of particle's current position[12] is denoted with $F(\boldsymbol{W})$, the coding structure would be adopted as follows.

$A_1, A_2, A_3, \cdots, A_n, B_1, B_2, B_3, \cdots, B_m$	$v_1, v_2, v_3, \cdots, v_{n+m}$	$F(\boldsymbol{W})$

Fig. 2 Coding structure in PSO algorithm

Since the PSO algorithm only depends on the fitness function to guide the search[13], it must be defined before the PSO algorithm is initialized. Mean square error is chosen as the fitness function in this study defined by

$$F(\boldsymbol{W}) = J = \frac{1}{N} \times \sum_{k=0}^{N} e(k)^2 = \frac{1}{N} \times \sum_{k=0}^{N} (r(k) - z(k))^2. \tag{12}$$

1.3 Principle of dynamic compensation of sensors based on PSO integrated with FLANN

The search speed of optimization method based on FLANN is high. However, it will fall into the local minimum easily during network training. Although PSO algorithm has high global search capability, its optimized results are easily affected by initial conditions. Combining the advantages and disadvantages of two optimization algorithms, the method based on PSO Integrated with FLANN is presented. With this method, the initial conditions of PSO can be determined by FLANN.

The steps of optimizing compensator's coefficients by PSO algorithm integrated with FLANN are as follows:

Step 1: Set initial parameters of FLANN, including inputs $\boldsymbol{X}(k)$, learning factor α, threshold b, desired value of MSE and training times;

Step 2: Train the neural network till training times or desired value of MSE is attained. Then save last coefficients $\boldsymbol{W}$;

Step 3: Set initial parameters of PSO algorithm, including population size, dimension, inertia weight, acceleration coefficients, position space and velocity space;

Step 4: Initialize every particle's position and velocity in parameter space through coefficients $\boldsymbol{W}$ in steq 2;

Step 5: Calculate the fitness function $F(\boldsymbol{W})$ using Eq. (12);

Step 6: Initialize the current particle's position as the individual extreme ***pbest***, and the position of particle with minimum fitness among all individual extreme as ***gbest***;

Step 7: Update the particle's position and velocity according to Eqs. (10) and (11);

Step 8: Calculate the fitness function $F(\boldsymbol{W})$ again;

Step 9: Judge whether to update the particle's individual extreme ***pbest*** and the global extreme ***gbest*** of particle swarm;

Step10: Repeat step 5 to step 7, till meeting precision demand or reaching iteration times, output ***gbest***, to obtain the coefficients of compensator.

2 Feasibility analysis on dynamic compensation of sensors based on PSO integrated with FLANN

Various important types of sensors like accelerometers or load cells can be modeled by Amass-spring system resulting in a second-order model[14] of the kind as

$$H(s) = \frac{s_0 \omega_0^2}{s^2 + 2\delta\omega_0 s + \omega_i^2}, \tag{13}$$

where s_0, δ and ω_0 denote static gain, damping and resonance frequency respectively.

In order to simulate dynamic performance of those sensors, a second-order analog filter has been designed and its circuit is shown in Fig. 3. We can simulate the characteristic of sensor through changing the parameters of resistance and capacitance.

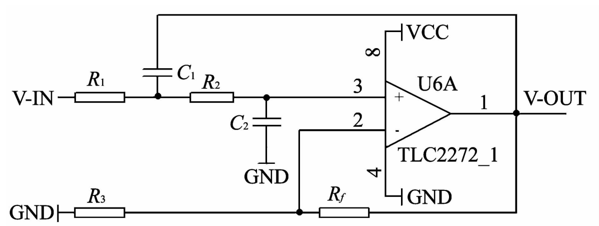


Fig. 3 The circuit of analog filter

In order to validate feasibility of the compensation method based on PSO integrated with FLANN, a square wave whose frequency is 200 Hz has been used as the analog filter's input. Then, the input and response of analog filter has been measured by test system. Using the input and response, we can get the coefficients $\boldsymbol{W}$ of compensator through the dynamic compensation algorithm. Take the $\boldsymbol{W}$ and response into Eq. (1), then, we can get the compensated result as shown in Fig. 4.

In Fig. 4, the amplitude has been normalized, sampling period of test system is 0.02 ms. From the compensated result we can see that the system response after compensation approached the input signal commendably, the speed of the dynamic response was enhanced, and the noises were reduced.

In order to analyze the effect of training samples on coefficients $\boldsymbol{W}$, ten groups of input and response of analog filter have been sampled by test system and the average of input and response have been calculated. Then, the compensators have been obtained by compensation algorithm through those samples and average, the frequency response of those compensators and error analysis are shown in Fig. 5 and Fig. 6.

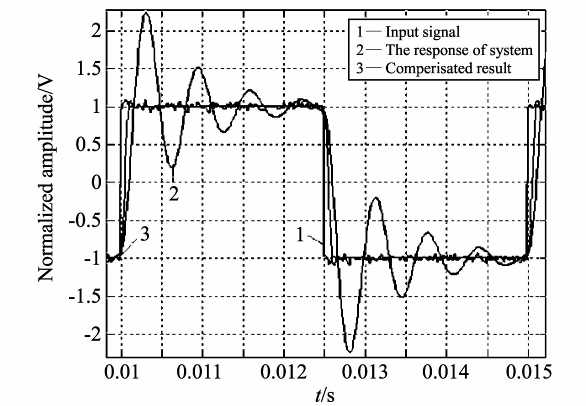
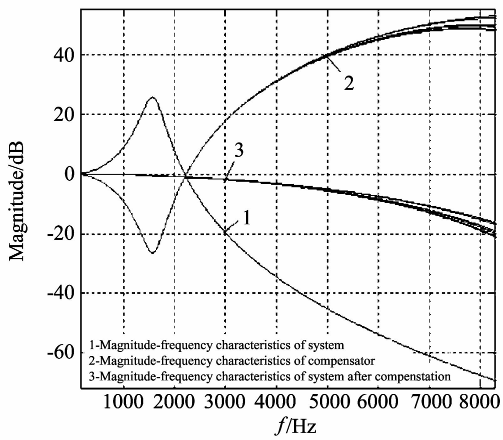
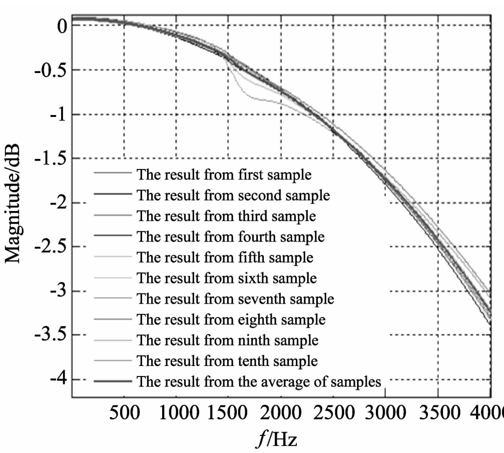


Fig. 4 Results of compensation



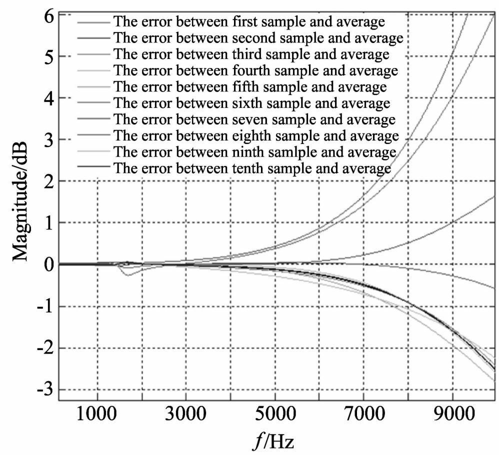
(a) Frequency response of analog filter and compensators



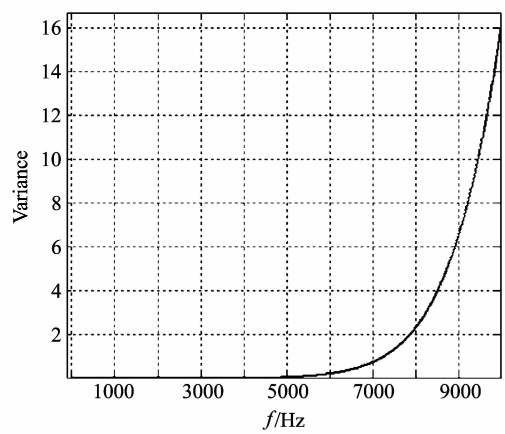
(b) Frequency response of system after compensation

Fig. 5 Comparation of frequency response

A comparison of the frequency response of the compensated systems in Fig. 5 shows that the compensator yields a good approximation to the inverse model of analog filter in the relevant frequency region, analog filter's working frequency bandwidth has been expanded and its dynamic performance has been improved. In Fig. 6, we can see the coefficients $\boldsymbol{W}$ have a less dependence on the input and output samples of analog filter from 0 to 6 kHz, and the error between samples' frequency response and average's frequency response is less than ten percent, that is to say if a sensor's dynamic model like the analog filter in Fig. 4 and widening bandwidth no more than 6 kHz in compensation, the compensation method based on PSO integrated with FLANN is available and efficient.



(a) Frequency response error between samples and average



(b) Frequency response variance of samples

Fig. 6 Error analysis of samples' frequency response

3 Conclusion

The primary outcome of the paper is the development of a dynamic compensation algorithm based on PSO integrated with FLANN to correct sensor's dynamic error caused by its systems limitation. The dynamic compensation algorithm can realize dynamic compensation without knowing the model of sensor; with this algorithm, we can avoid extra error caused by dynamic modeling of sensors. The algorithm has been demonstrated with a second-order system. It has been shown that the dynamic compensation algorithm based on PSO integrated with FLANN provides an accurate compensator in the relevant frequency region. Experimental results, showing the viability of the proposed algorithm, were presented.

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