Reinforced Quantum-behaved Particle Swarm Optimization Based Neural Networks for Image Inspection

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Abstract

The paper combines the niche particle concept and quantum-behaved particle swarm optimization (QPSO) method with chaotic mutation to train neural networks for image inspection. When constructing the reinforced quantum-behaved particle swarm (RQPSO) to train neural networks (RQPSONNs) for image inspection, first, image clustering is adopted to capture feasible information. Then the database of image can be built. In this research, the use of support vector regression (SVR) method determines the initial architecture of the neural networks. After initialization, the neural network architecture can be optimized by RQPSO. Then the optimal neural networks can perform image inspection. In this paper, the program of RQPSONNs for image inspection will be built. The values of root mean square error (RMSE) and peak signal to noise ratio (PSNR) are calculated to evaluate the efficiency of the RQPSONNs. Moreover, the experiment results will verify the usability of the proposed RQPSONNs for inspecting image. This research can be used in industrial automation to improve product quality and production efficiency.

Keywords: Quantum-behaved particle swarm optimization, Niche particle, Support vector regression, Image inspection

1. Introduction

The application of image inspection is quite extensive including medical science, machine vision, and predicting analysis of patterns in smart automation production fields.[1–5] The input images are first filtered by a high-pass filter, which is used to remove direct current and enhance high-frequency components. And then the filtered input images, which are overlapped rather than displaced from each other in the plane, serve as the input images.[6] Neural networks have the capacities of learning, adaption, and nonlinear mapping of images.[7]

The PSO algorithm possesses the ability of high convergent speed, easily falling in some local optima is its fatal defect. Many researchers have presented revised PSO algorithms and obtained good results.[8] Another improvement on traditional PSO algorithm is quantum-behaved particle swarm optimization (QPSO).[9] However, in QPSO, particles fall into local optimal state in multimode optimization problems and cannot find any better state.[10-12] To overcome the premature phenomenon in QPSO, a modified quantum-behaved particle swarm optimization (MQPSO) is proposed to identify nonlinear systems.[13] Authors proposed niche particle swarm optimization (NPSO) for image segmentation.[14] In NPSO algorithms, particles changing the place of the course to center the appropriate position (niche) of the particle will be absorbed. Then, particles amalgamate the small appropriate position (small niche) to become a large appropriate position (big niche).[15]

This paper combines the niche particle concept, quantum-behaved particle swarm optimization (QPSO) method with chaotic mutation to train neural networks for image inspection. When constructing the reinforced quantum-behaved particle swarm (RQPSO) to train neural networks (RQPSONNs) for image inspection.

2. Modified Quantum Particle Swarm Optimization

From the view of classical dynamics, to avoid explosion and guarantee convergence, particles must be bounded and fly in an attractive potential field. Clerc and Kennedy[8] have proved that if these coefficients are properly defined, the particle's position p_i will converge to the center of potential field, $pf^c = [pf_1^c, pf_2^c, \cdots, pf_n^c]$, and is defined as:

$$pf_i^c = \frac{(c_1 \cdot r_1 \cdot p_i^l + c_2 \cdot r_2 \cdot p^g)}{(c_1 \cdot r_1 + c_2 \cdot r_2)}, \ i = 1,2,\cdots,n. \quad (1)$$

where p_i^l and p^g are the best position of the ith particle and the global best position; c_1 and c_2 are cognitive and social constriction coefficients, respectively; r_1 and r_2 are random numbers between 0 and 1.

Inspired by the behavior that particles move in a bounded state and preserve the global search ability, Sun et al.[12] proposed the QPSO algorithm. In the QPSO model, the solution of time-independent Schrödinger equation for this system in one dimensional space can be expressed as:[10]

$$p_i = pf_i^c \pm \frac{L}{2} \cdot \ln\left(\frac{1}{\lambda}\right), \quad (2)$$

where λ is a random number uniformly distributed on [0, 1] and L is the characteristic length of delta potential well (called "Creativity" of particles) which specifies the search scope of a particle. The mainstream thought point and can be expressed as the following forms:[12]

$$mbest = \left[\sum_{i=1}^{n} \frac{p_{i,1}}{n}, \sum_{i=1}^{n} \frac{p_{i,2}}{n}, \cdots, \sum_{i=1}^{n} \frac{p_{i,n}}{n}\right], \ i = 1,2,\cdots,n, \quad (3)$$

$$L = 2 \cdot \beta |mbest - p_i|, \quad (4)$$

The creative coefficient β with adaptive annealing learning mechanism according to the change rate of optimal estimation has the form:

$$\beta = \beta_{max} - \Delta\beta \cdot (\Delta fit)^\gamma, \quad (5)$$

$$\Delta fit = |p^g - p_i^l|, \quad (6)$$

where $\Delta\beta$ is step length of β, Δfit is the change rate of optimal estimation so far. The mechanism of adaptive annealing learning can overcome the stagnation problem to accelerate the convergent speed.

3. Reinforced Quantum-Behaved Particle Swarm Optimization Neural Networks

3.1. Radial basis function neural networks

One can use a neural network to estimate the input–output relation of a dynamic system. In this paper, radial basis function neural networks (RBFNNs) are adopted because they have a simple structure, as shown in Figure 1. When the Gaussian function is chosen as the radial basis function, RBFNNs can be expressed in the form

$$\hat{y}_j(t+1) = \sum_{i=1}^{L} G_i w_{ij} = \sum_{i=1}^{L} w_{ij} \exp\left(-\frac{\|\hat{\mathbf{x}} - \mathbf{m}_i\|^2}{2\sigma_i^2}\right) \quad (7)$$

where $\hat{\mathbf{x}}(t) = [\hat{x}_1(t), \hat{x}_2(t), ..., \hat{x}_m(t)]^T$ is the input vector; $\hat{\mathbf{y}}(t) = [\hat{y}_1(t), \hat{y}_2(t), ..., \hat{y}_m(t)]^T$ is the output vector; w_{ij} is the synaptic weight; G_i is the Gaussian function; $\mathbf{m}_i$ and σ_i are the center and width of G_i respectively; and L is the number of the Gaussian functions, which is also equal to the number of hidden layer nodes.

Given a set of training input–output pairs $(\mathbf{x}^{(k)}, \mathbf{y}^{(k)})$, $k = 1,2,...,N$, the optimization problem of RBFNNs is to determine the values of w_{ij}, $\mathbf{m}_i$, and σ_i to minimize the index

$$J = \sum_{k=1}^{N} \|\mathbf{y}^{(k)} - \hat{\mathbf{y}}^{(k)}\|^2, \quad (8)$$

where $\hat{\mathbf{y}}^{(k)}$ is the corresponding output of RBFNNs when the input $\hat{\mathbf{x}}$ to the network is equal to $\mathbf{x}^{(k)}$
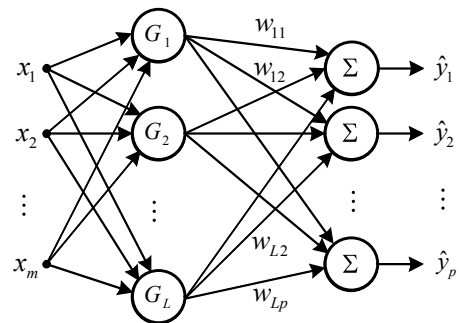

Fig. 1. The structure of RBFNNs.

3.2. Niche evolution

The appropriate position evolves (niche evolution) can solve the multimodal function optimization problems effectively.[16] Adopt the structure of appropriate position and search some local extreme values synchronously and avoid early convergence. It is difficult to determine the appropriate radius (niche radius) σ_{share}. Define the niche radius as follows:[17]

$$\sigma_{share} = \sigma_0 r e^{\left(-\lambda \frac{d_{avg}}{R}\right)} \qquad (9)$$

$$r = \max_{1 \le i \le N}\left\{|u_i - v_i|\right\} \qquad (10)$$

$$d_{avg} = \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}d(\varphi_i,\varphi_j) \qquad (11)$$

$$R = \sqrt{\sum_{i=1}^{N}\left(u_i - v_i\right)^2} \qquad (12)$$

where λ is an adjusting parameter, R is norm of $[u,v]$, σ_0 is the relative parameter of σ_{share}. d_{avg} is the average distance of particles.

3.3. *Chaotic mutation*

The Chaos phenomenon in nonlinear science means a kind of definite but unpredictable motion state. It has already been applied to optimizing stochastic optimization problems efficiently. This study adopts chaotic mutation operation to avoid falling into some local extreme value. The logistic equation of Chaos iterating is expressed as follows:[16]

$$\eta_j^{k+1} = \mu\eta_j^k(1-\eta_j^k) \quad k=1,2,\dots \qquad (13)$$

4. Simulation Results

In this paper, a work piece for image inspection is performed by the proposed RQPSONNs. The experiment results will verify the usability of the proposed RQPSONNs for inspecting image shown as Figure 2.

(a)   (b)

Fig. 2. (a) work piece on the conveyer belt (b) work piece finished inspection.

5. Conclusions

In the study, RQPSONNs combining the niche particle concept, quantum-behaved particle swarm optimization (QPSO) method with chaotic mutation to train neural networks is proposed to solve image inspection. Moreover, the experiment results will verify the usability of the proposed RQPSONNs for inspecting image.

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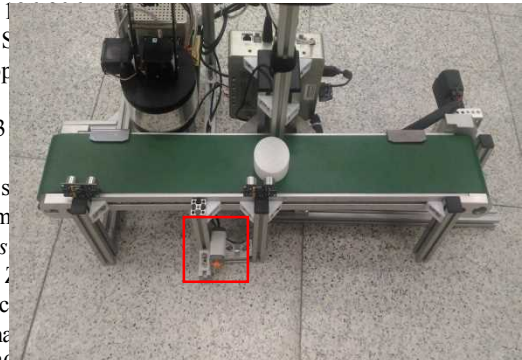
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