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A Prediction Method of Soybean Moisture Content in the Process of Soy Sauce Brewing Production Using Quantum Revolving Gate of Quantum Evolution Algorithm Back Propagation

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Abstract: Soybean fermentation is a key of production of soy sauce, and directly affects its quality. In order to solve the problem of slow convergence speed and low error precision in VLBP, a new model of optimized VLBP by quantum revolving door of quantum evolution algorithm has been proposed. The model and algorithm are performed the quantum-behaved data into input-layer of VLBP which is transformed by the principle of phase shift in the quantum behavior theory, and the weigh data is performed a controlled-NOT gate as the output-layer input to reform the forward transmission. With the steepest descent method, the information is transferred by the error back propagation perform updating the weighs in the hidden-layer and output-layer by involving the controlled-NOT gate's transfer function. Finally, the trained algorithm has been used for forecasting the soybean moisture content of soaking time and temperature using the R-QEABP and VLBP neural network algorithm. Compared with VLBP, the results have been indicated that the R-QEABP has great advantages of convergence speed, lower verify error, and better robustness for the purpose of realizing the accurate prediction of soybean moisture content in the process of soy sauce brewing production.

1. Introduction

Soy sauce is a traditional fermented condiment and its brewing in China has a long history. The preparation of processes including dipping, steaming, microbial cultivation and fermentation, and steaming, are the key process in the production of soy sauce. The degree of water in soy plays an important role to providing a strong guarantee for continuous steaming process.

The Soybean moisture content is a direct factor to reflect the dipping degree which would affect the quality and vitality, which may avoid the temperature being too high to promote nutrient to decompose so easily that cause fever, mildew, germination, and prevent the low temperature form which destroying the structure and stopping the metabolism without any nutritional value. Therefore, in order to keep the quality of soy sauce and feed the requirements of the continuous steaming process, Lee Kum Kee (Xinhui) Food Co. Ltd., takes the advantage of the technologies employed by mechanization and automation as well as design, with the development of continuous soybean dipping tank equipment, monitors the soybean moisture content online through the electronic weighing device of cylinder pounds of dried beans as well as the conveyor belt of soybean.

The time and temperature of the dipping soybean is a major factor in the continuous soybean dipping process. It is difficult to find relationship among the time, temperature, and moisture content owning to the nonlinear error exists in the practice of machining and testing. A slew of nonlinear error analysis of system show that it is contradicted to the fact, but predicting the error is not beyond a measure of control through consulting literature materials.

Artificial neural network (ANN) is a information processing and computing system which is based on the modern neuroscience research[1,2], overcomes the above mentioned simultaneous problem without accurate model to acquire the characteristic by data mining and nonlinear mapping of the system. And the variable learning rate backpropagation (VLBP) has widely applications and it also has massive problems, such as slow rate of convergence, more iterative times and low accuracy of error and so on.

The quantum mechanics technology may be blended in the VLBP to help performance even more[3]. Recently, the research on quantum artificial neural network combines the quantum and algorithm theory is an important leading edge in the field. It also can increase the ability of approximate accuracy of network[4,5], pattern recognition and optimization of PID parameters[6,7]. But there is not many studies on predictions about the soybean moisture content, having not progressed beyond the preliminary stage.

Therefore, mining the data of the time and temperature form in the experiment of dipping soybean based on the cording principle and combining the quantum which is transformed by the principle of phase shift in the quantum behavior theory and VLBP artificial neural network, whose weigh data perform a controlled-NOT gate as the output-layer input to reform the forward transmission, can forecast the soybean moisture content continuously with less iterative times with high accuracy in comparison with BP and VLBP algorithms.

2. Materials and Methods

2.1 Materials

Soybean: Certificate of origin in Hei Longjiang, the basic physicochemical index: 11% moisture content, crude fat content 18.4% , ash content 4.6%, crude fiber content of 0.48%, the crude protein content of 36.1%, nitrogen solubility index XX%.

2.2 Methods

It was assumed the time and temperature as the experimental factor, the time period was 80-140 min. The temperature data was recorded by the temperature sensor and the actual moisture consistent through infrared moisture meter which was the subject of the main part of the experiment. The data was of 30 groups which were randomly selected from the data of the 150 groups. Thus, the time and temperature as well as the true moisture content were calculated by VLBP and R-QEABP, respectively. The selection was about 30 groups from the rest of 120 groups of data as the test part which could be used to check the VLBP and R-QEABP algorithm by analyzing the relationship among the test error and the learning rate, the convergence error and the number of iterations, the number of iterations and the target error, and the execution time and the target error to compare with the effects of these two algorithms, and an efficient and accurate compensation algorithm would be found finally.

3. R-QEABP

3.1 Quantum computing theory

In quantum mechanics, when the state of a particle at a given moment is known, the state of the particle is determined by the following Schrodinger equation as,

$$i\hbar\frac{\partial}{\partial t}\psi(\mathbf{r},t)=\left(-\frac{\hbar}{2m}\nabla^2+V\right)\psi(\mathbf{r},t) \tag{1}$$

Where ψ is the wave function, m is the mass, V is the potential energy of the particle in the force field, $\hbar$ is the Planck constant, and ∇^2 the Laplace operator which is defined as $\nabla^2=\frac{\partial^2}{\partial x^2}+\frac{\partial^2}{\partial y^2}+\frac{\partial^2}{\partial z^2}$

In classical computing, 0 and 1 as the binary numbers to represent information, usually referred to as bits, can only be in the "0" or "1" in two states. However, in the quantum computation based on the Schrodinger equation, there are the two basic states ("$|\ \rangle$" as the symbol of the "Dirac"), combined by the superposition of states linearly:

$$|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{2}$$

$$|\alpha|^2 + |\beta|^2 = 1 \tag{3}$$

The above eq. (2) and eq. (3) were satisfied the Schrodinger equation of wave function argument, which is a complex, known as quantum probability amplitude, can be expressed as $[\alpha \ \ \beta]^T$. The eq. (2) shows that the quantum state $|\varphi\rangle$ will collapse to the state $|0\rangle$, due to the probability $|\alpha|^2$ of its measurement, or collapse to the state $|1\rangle$, due to the probability $|\beta|^2$ and it may be expressed in any states that satisfies in the statement as: in quantum computation, quantum gates are unitary operations used to describe the evolution of quantum states in a certain time, as the device to transform the quantum states, the basis of quantum computation.The quantum state $|\varphi\rangle = (\cos\mu \quad \sin\mu)^T$ ($\cos\mu = \alpha$, $\sin\mu = \beta$ are satisfied the structural formula of 1-3 quantum phase), and quantum revolving gate ($\mathbf{R}(\theta)$),$|\varphi\rangle$ under the effect of the $\mathbf{R}(\theta)$, as shown in the following:

$$R(\theta)|\varphi\rangle = (\cos(\mu+\theta) \quad \sin(\mu+\theta))^T \tag{4}$$

Based on the quantum computation, the unitary matrix, $\mathbf{U} = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$ under the effect of C-NOT gate which can be stated as:

$$\mathbf{U}|\varphi\rangle = \begin{pmatrix} \sin\mu \\ \cos\mu \end{pmatrix} = \begin{pmatrix} \cos(\pi/2-\mu) \\ \sin(\pi/2-\mu) \end{pmatrix} \tag{5}$$

According to the quantum theory about the revolving gate, the eq. (4） can be transformed as in the following:

$$\mathbf{U}|\varphi\rangle = \mathbf{R}(\pi/2-2\mu)|\varphi\rangle \tag{6}$$

Therefore, the C-NOT gate under the effects of the revolving gate can be transformed as in the following:

$$\mathbf{G}(k) = \begin{pmatrix} \cos(k\pi/2) & -\sin(k\pi/2) \\ \sin(k\pi/2) & \cos(k\pi/2) \end{pmatrix} \tag{7}$$

The above is the knowledge of quantum computation theory to improve the algorithm to concentrate on such aspects as:

(1) Study on the model of traditional neural network transformation by quantum computation;

(2) There is a beneficial performance effect from parallel operation and acceleration of quantum computation to drive up the performance by the quantum revolving gate;

(3) Quantum computation is proposed to be applied in the transformation for a new neural network algorithm.

3.2 R-QEABP

Quantum neural network theory based on VLBP improved by quantum evolutionary algorithm applied on the revolving gate (R-QEABP) involves input, phase transformation, aggregation structure, quantum output weighted transmission and the output five parts, in addition the back propagation includes the reverse transmission error to the weighted coefficient and the quantum rotation angle coefficient, as shown in Figure 1.

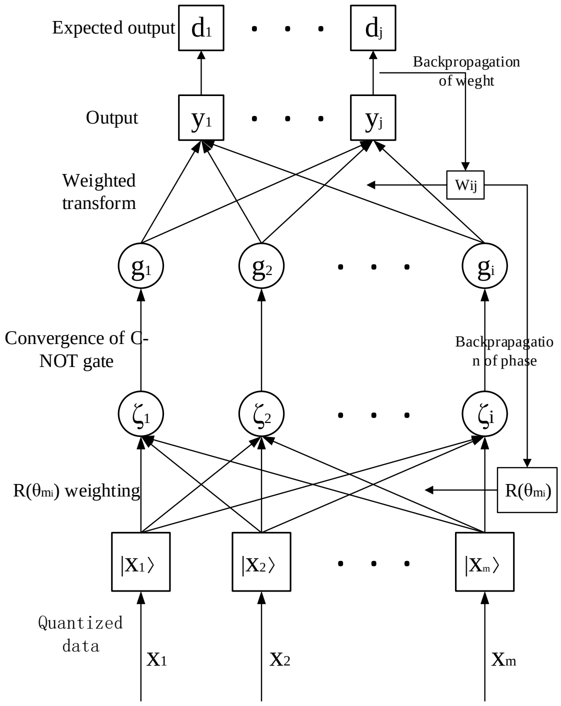

Figure 1: The flow diagram of the algorithm

The above is the fundamental of R-QEABP and the steps as follow:

Step 1: Change the data with the principle of quantum computation;

Step 2: Under the effects of quantum superposition the phase of data can be transformed and extracted from the weight as the controlled parameter of C-NOT gate;

Step 3: The controlled parameter would be used into sigmoid function and quantum C-NOT transformation formula as the hidden layer output operation;

Step 4: Through the sigmoid function, the output of the hidden layer of the traditional VLBP would be weighted;

Step 5: The weight of the phase and the output can be adjusted by the difference between the expected output and the network, with the steepest descent back regulation;

Step 6: Continuously update to meet the network error accuracy.

4. Analysis of test data

The results show that the quantum revolving gate modified VLBP has a better effect on the nonlinear compensation about the soybean moisture content. The control of process is a complex multivariable control system, and the key control objects of the system for the moisture content of soybean, and the temperature as well as the time of dipping beans. The experimental data is detected by the infrared moisture on-line production rate in Lee Kum Kee (Xinhui) Food Co. Ltd. (real water content).

It is difficult to determine the relationship between the time and the temperature of the dipping bean, the relationship between the moisture content and the time, and to establish a mathematical model to predict the moisture content of soybean. Based on the neural network theory, a new network model has been applied in the quantum computation which may be established to analyze the relationship between the bean moisture content time and temperature with the rate of 1% nonlinear error compensation accuracy.

In order to reflect the superiority of quantum evolutionary algorithm, the improved VLBP (R-QEABP) of quantum revolving gate is compared with the BP (VLBP) algorithm with variable learning rate, would be checked by the test data by choosing the same structure and parameters.

(1) To make a relationship between test error and learning rate, the target error is 1%, recording the errors on the condition with different learning rate as 0.1, 0.2, 0.3,... 1. Taking 100 iterative times, it can be found the relationships of the results which are shown in Figure 3.

The Figure 2 shows the different variation of learning rate between the test error of VLBP and R-QEABP. As shown in the Figure 2, the test error decreases, with the learning rate raising. The R-QEABP test errors in the same learning rates are smaller than VLBP and R-QEABP, it can be decreased to test a low error of the learning rate in the ranges of 0.4-0.6, while the VLBP is decreased in the ranges of 0.4-1.0. In short, R-QEABP has a faster convergence speed.

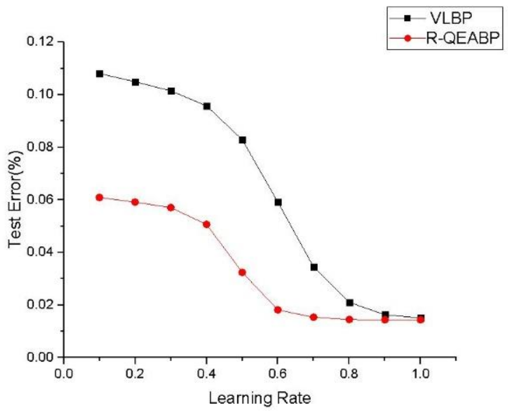

Figure 2: The test error of VLBP and R-QEABP

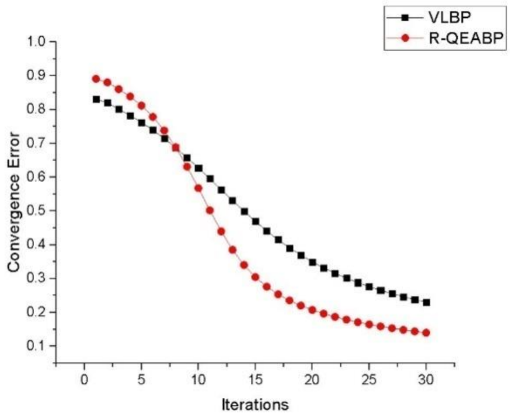

Figure 3: The convergence error of VLBP and R-QEABP

(2) The relationship between convergence error and iteration times are indicated with setting the target error to 1%. The convergence error of VLBP and R-QEABP are observed in 30 iterative times. The results are shown in Figure 3.

As shown in Figure 3, when the number of iterations is increasing, the errors of VLBP and R-QEABP are converging. In the same iteration, from the first to seven iterations the error of R-QEABP is greater than VLBP, under other circumstances the error is smaller. The results show that the convergence efficiency of R-QEABP is better in the same iterative times.

(3) The relationship between the times of iterations and the target error. Setting the same learning rate as 0.3, recording the times of iterations, VLBP and R-QEABP, whose target errors were as 1%, 2%, 3%,..., is used to compare the various methods, and the results shown in Figure 4.

Compared with VLBP algorithm, the experimental results show that R-QEABP achieves higher performance with the higher accuracy and speed of convergence as well as robustness of R-QEABP is proposed to be better under the same conditions.

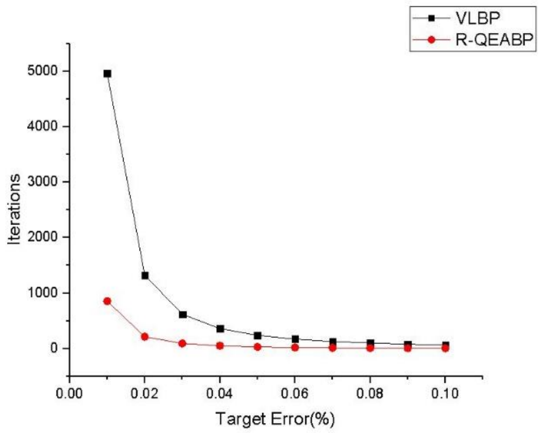

Figure 4: The times of iterations of VLBP and R-QEABP

5. Conclusions

A new neural network based on quantum computation with revolving gate theory is proposed to predict the measurement of soybean moisture content continuously. R-QEABP puts the quantum-behaved data into model applied on the revolving gate and improves the abilities of parallel computation and high speed of convergence. The superiority of R-QEABP is proved on the fields of test error, convergence error, the times of iterations and executions time and the model is more consistent with the dictation of the soybean moisture content. compared with VLBP, the results is indicated that R-QEABP has great advantages of convergence speed, lower verifying error as well as better robustness for the purpose of realizing the accurate prediction of soybean moisture content in the process of soy sauce brewing production.

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