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RESEARCH ARTICLE

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Application of BP neural networks in non-linearity correction of optical tweezers

Abstract The back-propagation (BP) neural network is proposed to correct nonlinearity and optimize the force measurement and calibration of an optical tweezer system. Considering the low convergence rate of the BP algorithm, the Levenberg-Marquardt (LM) algorithm is used to improve the BP network. The proposed method is experimentally studied for force calibration in a typical optical tweezer system using hydromechanics. The result shows that with the nonlinear correction using BP networks, the range of force measurement of an optical tweezer system is enlarged by 30% and the precision is also improved compared with the polynomial fitting method. It is demonstrated that nonlinear correction by the neural network method effectively improves the performance of optical tweezers without adding or changing the measuring system.

Keywords optical tweezers, back-propagation (BP), nonlinearity correction

1 Introduction

The interactions of micro-particles determine the dynamics of particles. For example, in microbiology, people are trying to understand the process of life at the level of bio-macromolecules where force is an important parameter. In a typical soft matter-disperse system, the interactions of particles in the disperse phase affect macro-behavior. The interactions related to the mechanical nature of micro-particles and the interactions among particles with biomacromolecules included generally involve measurement at the level of piconewtons. Thus, a reliable and accurate method of measuring the tiny force is of significance.

Measurement with optical tweezers [1,2] is based on the interaction between light and micro-particles, i.e., the relationship of the force upon the micro-particles and the position in an optical trap. The theory and experiment [2–4] show that for different optical traps formed by different optical beams, a slight lateral displacement of the bead yields a good linear relationship of the lateral optical trap efficiency and the particle position. Hence the region is called a harmonic region. When involving the large force, the relationship between lateral force and displacement of the particles does not exhibit any linearity.

In terms of ease and accuracy, the measurement of optical tweezers is usually limited to the use of a linear region. The relationship of the trapping force and displacement is then simply calibrated by a coefficient of linear fit called the stiffness of optical trap [5]. However, the only use of this linear range limits the zone of the measurement.

If the relationship of the optical trapping force and displacement can be calibrated, we can obtain an accurate measurement for the force in the large range. If the non-linear correction is included in the measurement system and the calibration and measurement of output value in the entire range with a linear relationship, we can expand the effective linear range of the force measuring of the optical tweezer system. In earlier studies, a triple polynomial has been used to fit the non-linear relation of optical trapping force and displacement of the particle [2,6,7]. Although the relation can be measured using the scope of harmonic areas and expands the range of the force measurement system, this method lacks accuracy.

The range and accuracy of force measurement are the most important parameters of the optical tweezer system. Recently, research and application of neural networks (NNs) has been in progress. As artificial neural networks have significant nonlinear mapping capabilities and are able to approach any continuous function with arbitrary accuracy [8], more NNs now use calibration of the

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response characteristics of non-linear sensors. This realizes correction of the nonlinear response, improves accuracy and expands the scope of an effective linear range [9,10]. In view of the inherent relationship of the optical trapping force and the displacement of the particle in the trap, an NN-based method is proposed to calibrate and correct the non-linear response region of optical tweezers to expand the range of measurement without changing any hardware condition.

2 Back-propagation (BP) networks and improved algorithm

Almost all neural network models adopt a BP network or its transformation in their application. A BP network is the core of a feedforward network as well as the essence of neural networks.

2.1 BP networks

BP networks are a kind of multilayer feedforward network. A typical BP neural network is composed of an 'input layer', 'hidden layer' and 'output layer'. The 'input layer' is the input of the BP network, where each input node and its adjacent hidden layer nodes are all connected. The hidden layer is the reality layer of the learn function, where the signal of the net forward transfer observes the principle that each node of the upper layer and all nodes of the lower layer are connected. The output layer integrates the approached results from the hidden layer and obtains the final output.

The correct number of hidden layers and nodes is important when designing a neural network. However, at present no ideal method is available. Generally, with learning samples and testing samples, the network structure of an error is analyzed by cross-evaluation and by selecting the appropriate network structure with the trial and error method. Increasing the number of hidden layers can reduce errors and improve accuracy, but it also makes the network more complex and increases the training time for the weight of artificial neural network. Another way of improving error precision is to increase the number of neurons. Generally, the number of hidden layers is usually set as 1–3. In this article, it is set as one. The typical S-function is selected for the neurons of hidden layer and output layer:

$$f(s_j) = \frac{1}{1+\mathrm{e}^{-T_j s_j}}, \; s_j = \sum_{i=0}^{N} x_i W_{ij}, \tag{1}$$

where T_j is the adjusting coefficient of neurons, usually set from 0 to 1; x_i is the ith input from the upper layer nodes; and W_{ij} is the connection weight value of the ith neurons from the upper layer and the jth neuron. When $i = 0$, the weight value is called the threshold.

2.2 Improvement of learning algorithm of BP NNs

BP network learning is typically a learning algorithm with a tutor, a basic learning algorithm: the BP learning algorithm, which is an enhancement of learning rules. The BP learning algorithm is simple and practical, but its convergence is slow and it is susceptible to a local minimum point. Therefore, various alternatives have been proposed to improve it, including genetic algorithms, rapid decline in law, and the Levenberg-Marquardt (LM) algorithm. In this research, the LM algorithm is adopted.

The LM algorithm is essentially a quadratic gradient algorithm combining the steepest decent algorithm with the Gauss-Newton algorithm. On the one hand, for the arbitrary quadratic function, the minimum value can be obtained through just one iteration regardless of the initial point's location; on the other hand, the non-quadratic function is similar with the quadratic function in the vicinity of the minimum point, and can thus easily obtain the minimum value.

The algorithm is as follows:

Assume $\boldsymbol{x}_k$ is the vector composed of weights and biases at the iteration k. For the new vector $\boldsymbol{x}_{k+1}$:

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k - (\boldsymbol{H} + u_k \boldsymbol{I})^{-1} g, \tag{2}$$

where $\boldsymbol{I}$ is the identity matrix. When $u_k = 0$, it is Newton's method. When u_k is large enough, it approaches the steepest decent method.

The Hessian matrix is

$$\boldsymbol{H} = \boldsymbol{J}^{\mathrm{T}} \boldsymbol{J}, \tag{3}$$

where $\boldsymbol{J}$ is the Jacobian matrix of first derivatives of the residuals. The gradient can be expressed as

$$g = \boldsymbol{J}^{\mathrm{T}} e. \tag{4}$$

Placing Eqs. (3) and (4) into Eq. (2), we can get the LM algorithm

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k - \left(\boldsymbol{J}^{\mathrm{T}} \boldsymbol{J} + u_k \boldsymbol{I}\right)^{-1} \boldsymbol{J}^{\mathrm{T}} e. \tag{5}$$

3 Calibration of mechanical property of optical tweezers [11,12]

Nano-optical tweezers can be used to measure the displacement of micro-sized particles with nanometer accuracy. The key of measuring forces using optical tweezers is the calibration of its mechanical properties, i.e., the relationship of the restoring force and the bead displacement departing from the equilibrium position. This relationship is linear near the center region, when the mechanical properties are simplified as calibration of the stiffness of the trap.

In practice, trapping and manipulation of micro-sized particles is done in aqueous solutions. Thus, the dragging force method commonly used to calibrate the stiffness is adopted. Based on the Stokes law, when moving the trapped bead in a certain velocity, the viscous force is given by

$$F_{\text{vis}} = -6\pi\eta r v, \tag{6}$$

where r is the bead radius, η is the medium viscosity, and v is the dragging velocity. When the viscous force equilibrates the trapping force of the bead, the bead departs from the center to a new position. The departure x can be measured by image correlation. Since the trapping force equilibrates the viscous force, the trapping force can be calculated by Eq. (6). The bead position varies with the trapping force and the viscous force and their relationship can be obtained. In the region close to the trap center, the relation between trapping force and displacement approximates linear as follows:

$$F_{\text{trap}} = -k_x \cdot x, \tag{7}$$

where k_x is the stiffness of the trap.

The experimental set-up and methods are as follows:

The optical micro-manipulation system used in our experiment is schematically shown in Fig. 1. It consists of three parts: optical components, manipulation system, and probing system. Optical components consist of the formation part of the optical trap and the microscopic observation part. The latter is similar to a microscopic objective, while the former is described as follows.

The optical trap is formed by a tightly focused He-Ne laser beam (10 mW, 632 nm, polarized, coherent, USA), which is directed to the inversed microscopy (Olympus IX70) before beam expansion and expands the beam to overfill the objective of the microscopy. The beam is then transmitted to a 100 × oil immersion objective (N.A = 1.35) and focused on the chamber to form an optical trap.

The manipulation adopts a passive mode controlled by the sub-nano piezo-scanning stage (P-517.3CL, PI, Germany), which adopts passive mode manipulation and moves the chamber at a certain velocity or to a certain position, with a range of 100 μm × 100 μm × 20 μm and accuracy of 1 nm. The trapping center is immobile in the experiment, which enables manipulation of the movement of the trapped particle relative to the surrounding medium.

The movement of the particle is observed with a CCD camera (CoolsnapCF mono camera, USA). The displacement is calculated by correlation analysis of the image series with an accuracy of 1 nm.

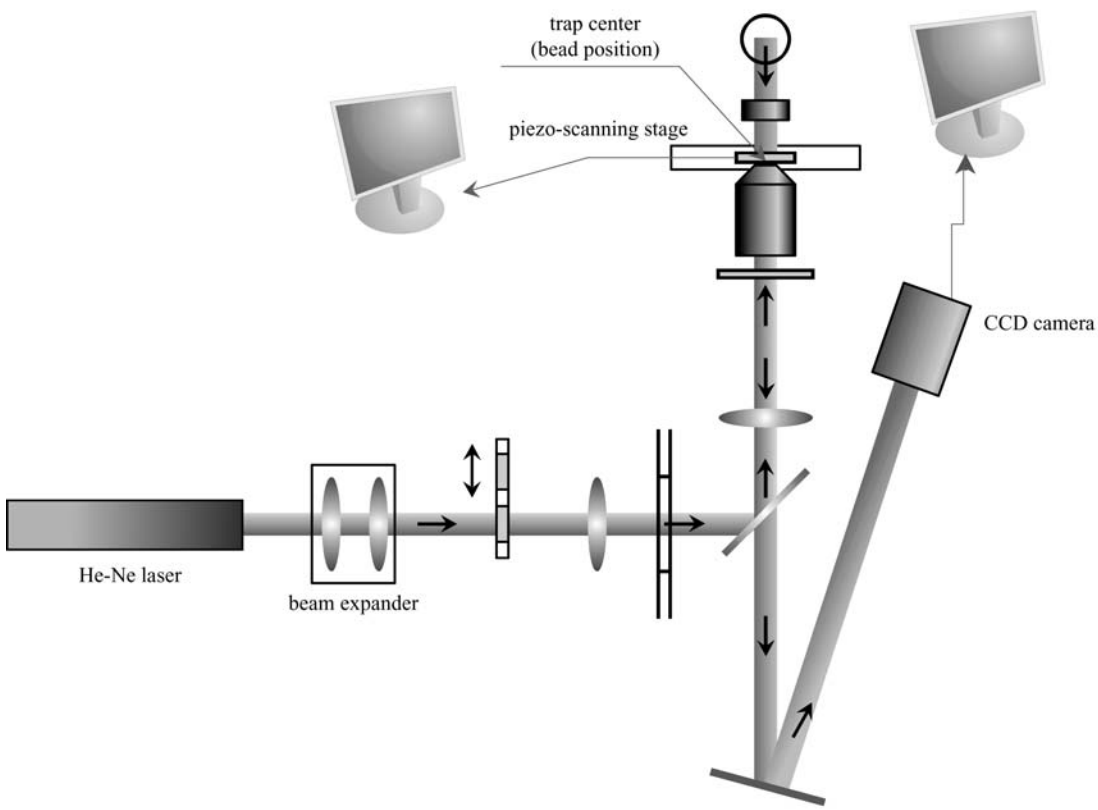

Fig. 1 Experimental set-up

The stage is moving with a constant velocity, while the particle moves reiteratively within the two equilibrium positions, which are obtained by correlation analysis of the particle's microscopy image series [1,9]. In this case, the relationship between the velocity of the bead and the displacement from the center can be measured. For a given velocity, the displacement is calculated by a series of 1000 images taken from the trapped bead. Using the aforementioned method, the relationship of fluid velocity v and displacement x can be measured at different velocities. From Eq. (6), the distribution of the trapping force $F_{\text{trap}}(x)$ can be obtained.

4 BP network training and test

We obtained the force field $F_{\text{trap}}(x)$ of the optical trap through the calibration method as mentioned above, i. e., with different velocities of the platform, the relationship of the optical force on the bead and the displacement of the bead are offset from the trapping center. The data when the experiments are conducted are shown in column F and x in Table 1, where F is the basis of the viscosity of the fluid and is equal to the trapping force in the balance state. x is the displacement of the bead offset from the center of the optical trap. All the data are taken as the sample data to train neural networks.

Table 1 Input and output signal of optical tweezer calibration and results of non-linear correction

No.	F/pN	x/μm	F_{nn}/pN	F_{cf}/pN
1	0.1159	0.0157	0.1159	0.1125
2	0.2318	0.0323	0.2318	0.2332
3	0.3478	0.0536	0.3478	0.3690
4	0.4637	0.0669	0.4636	0.4484
5	0.5796	0.0873	0.5797	0.5688
6	0.6955	0.1079	0.6954	0.6974
7	0.8115	0.1217	0.8116	0.7930
8	0.9274	0.1435	0.9272	0.9667
9	1.0433	0.1526	1.0436	1.0493
10	1.1592	0.1634	1.1591	1.1585
11	1.2752	0.1756	1.2757	1.2960
12	1.3911	0.1801	1.3909	1.3502
13	1.5070	0.1898	1.5074	1.4780
14	1.6229	0.2020	1.6230	1.6564
15	1.7389	0.2069	1.7390	1.7336

Through the trial and error method, a 1-7-1 network is adopted. The S-function is selected as the neuron function of the hidden layer, while the error sum of squares is set to be $E = 0.000001$. The training and test of neural networks are addressed by the neural network toolbox of Matlab 7.01.

After 303 trainings, the neural network reaches the goal and the error sum of the squares is 6.35106×10^{-7}. The approximation function derived by the BP network is shown in Fig. 2. Simulations show that the output of the neural network approximates to the objective cure line '+'. It is also demonstrated that the neural network has better fitting and generalization, and the process is of convergence. The relationship between error and training times is shown in Fig. 3.

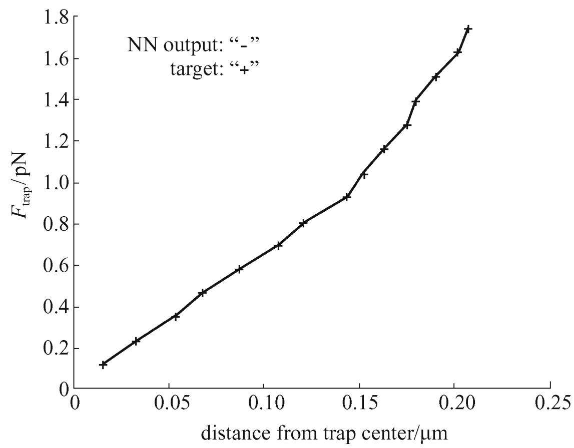

Fig. 2 Approximation function derived by BP network

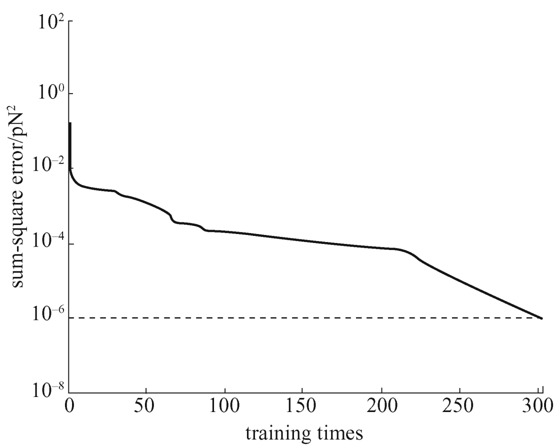

Fig. 3 Relationship between error and training times

Establishing the inverse model of a sensor with its function trained by the neural network, we derive the corresponding force from the displacement offset from the center of the optical trap, as shown in the F_{nn} column in Table 1, where the data when the polynomial fitting method (shown in F_{cf} column in Table 1) was used is also listed. As shown in Table 1, under the same experimental conditions, the accuracy of the results obtained with neural networks is 0.001 pN and 0.01 pN with the polynomial fitting method. The experiment data shows that both methods are able to accomplish the nonlinear correction, while the BP neural network method is much better than the polynomial fitting method.

Figure 2 also shows that the experimental data and theoretical data basically agree. The data have a certain fluctuation error because the experimental process is affected by the state of the system and the environment. These errors are from the system and data collection. The error caused by the system can be decreased by the BP neural network nonlinear correction. The data collection errors can be decreased by increasing the accuracy of collection equipment and the number of data collected for processing. Figure 2 shows that the range of the linear approximation is enlarged from 0–0.3r to 0.41r by the neural network. As long as the optical trap catches the bead and maintains stability, the calibration optical trap can be used. However, theoretical and experiment evidence prove that when approaching 0.6r, the trapped particles will escape from the vertical direction. Thus, the calibration range can only be within 0.6r.

5 Conclusions

The BP neural network is proposed to realize nonlinear correction for the force of optical tweezers, which enlarges the measuring scope of an optical tweezer system and improves the accuracy of measurement. Under the same conditions of optical power, the range of measurement is enlarged and requirement for hardware is reduced. Its application has significantly improved performance indicators of the optical tweezer system.

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