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Error compensation based on BP neural network for airborne laser ranging

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ABSTRACT

This paper proposes a general realization method of laser ranging for micro UAVs, which is based on secondary development for the laser ranging module of FLUKE 411D. And the airborne dynamic laser ranging experiments are finished with the micro UAV DJI Phantom1. Through data processing with the least-square-based method and BP neural network-based method, the measurement error with BP neural network-based method is obtained for 4.35%, which is significantly less than that 6.69% with least-square-based method. It means that the measurement accuracy is improved significantly with BP neural network-based method. Therefore, the error compensation method based on BP neural network for airborne laser ranging is verified effectively in the paper.

1. Introduction

The technology for rotorcraft unmanned aerial vehicle (RUAV) is developing rapidly in recent years. Compared with the fixed-wing unmanned aerial vehicle, it is better for RUAV on flight modes, including vertical take-off or landing, hovering, pirouette, bank-to-turn and lateral flight [1,2]. Light detection and ranging (LIDAR) is the critical equipment just like 'the eye' of UAV, and is employed to realize various of sensing applications for UAV [3]. And laser rangefinder (LRF) is one of the most important components for LIDAR. It sends a signal such as optical, radio and ultrasonic, onto a target object. With the reflected signal, the distance between the laser and the target is measured. For laser ranging, pulsed time-of-flight (TOF) and phase-shift are mainly two measurement principles [4,5]. The former method is to measure the interval time between the sent pulse and the received pulse. For pulsed TOF laser ranging, those factors including the total noise in the receiver channel and the slew rate of the pulses, greatly influence the precision of a single-shot measurement. For the latter phase-shift laser ranging, the phase shift between the transmitted pulse and a sinusoidal modulation reference signal are employed to measure the distance. And the crosstalk between the emitting circuit and the receiving circuit is the core concerned problem for phase-shift laser ranging. With low cost and mature development technology, most LRF products are phase-shift laser ranging on the market.

Nowadays, with new electronic components and electro-optical emerging technology, the effects from ambient lighting condition or other factors, have been reduced for precision laser ranging in a complex environment [7]. This noncontact measuring method that laser ranging is widely applied for three-dimension vision, positioning or level control, etc. [8,9]. For example, LRFs are commonly adopted for navigation tasks of mobile robots [10]. Generally, a LRF realizes the real-time and accurate range measurement in large angular field via being fixed at a certain height. And then simultaneous localization and mapping (SLAM) is achieved with the information fusion of camera image and LRF distance [11,12]. Furthermore, laser ranging is also available in many other fields as outdoor navigation system and description of urban environments, etc. [10,13–16].

It is always significant to get more accurate measured data for LRFs, which is more helpful to complete above tasks. Especially for the flight dynamic measurement, the error is more inevitable due to the UAV vibration, noise etc. It increases the nonlinearity of measured data.

During the last two decades, artificial neural network (ANN) algorithms have been developed rapidly for universal function approximations, including a function and its derivatives approximation, the failure probability of pipework prediction, the structural reliability analysis of a mine pillar, etc. [17]. For a long time, the adjustment question of connective weight in hide layer for ANN algorithm had not been solved until the error

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back-propagation (BP) algorithm was proposed later. BP neutral network is effective to reduce the nonlinearity of continuous function [18,19]. In literature [20], authors propose the method based on the least-square method to compensate the error for static measurement of LRF. Considering the nonlinearity for the flight dynamic laser ranging of RUAV, this paper proposes a novel error compensation method based on BP neutral network. And the experiment of airborne phase-shift laser ranging is completed to verify the proposed method [21,22].

To sum up, this paper proposes a BP neutral network-based approach to compensate the dynamic measurement error for airborne phase-shift laser ranging. The theory and methodology are stated in Sections 2 and 3. Then an airborne laser ranging prototype is proposed to achieve the flight experiment. Measurement data is processed and analyzed with the least-square and BP neutral network-based methods in Section 4. Finally, summary and prospect are given for the next work in Section 5.

2. Bp neutral network algorithm

ANN is established by referring to the structure and characteristics of human brain, which is interconnected with a large number of simple processing units. And ANN is a nonlinear dynamical system to realize large-scale parallel distributed information processing. Compared with conventional information processing methods, ANN has some characteristics including structure variability, high nonlinearity, self-learning and self-organization, etc.

In the year of 1986, Rumelhart et al. proposed BP neural network algorithm, which has been one of the most widely used network algorithm nowadays. Error back-propagation divides the learning process to two stages. The first stage is forward propagation. Via the input layer, the input is processed by the hidden layer to obtain the actual output of each unit. The second stage is back propagation. If the output layer can't get the expected value, the error, that is, the difference between the actual output and the expected value, is layer-by-layer calculated recursively. Then the error is used to adjust the weight. The structure of BP neural network is shown in Fig. 1.

It is proved that a BP neural network with hidden layers can approximate any nonlinear continuous function with any accuracy. Then define a BP neural network with L hidden layers and n units. Each unit just receives the outputs of previous layer, and outputs to the units of the next layer. In order to simplify the network, assume there is one output y for the whole network. Define m samples (x_k, y_k) ($k = 1, 2, \ldots, m$), and the output o_i of any unit i. For an input x_k, the output of the unit is o_{ik}, and the output of the network is y_k. Define unit j of layer l, and the input of unit j with k samples inputs is shown in the following equation:

$$p_{ij}^{l} = \sum_{j} w_{ij}^{l} o_{jk}^{l-1} \tag{1}$$

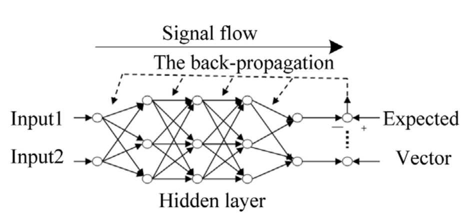

Fig. 1. The structure of a BP neural network.

where w_{ij}^{l} is the weight coefficient, and o_{jk}^{l-1} represents the output of unit j on the layer $l-1$ with k input samples. Then the output of unit j on the layer $l - o_{jk}^{l}$ can be calculated in the following equation:

$$o_{jk}^{l} = f\left(p_{jk}^{l}\right) \tag{2}$$

Define the error function E_k in the following equation:

$$E_k = \frac{1}{2}\sum_{l}\left(y_{lk} - y'_{lk}\right)^2 \tag{3}$$

where y'_{lk} is the real output of unit j on the layer l. Then the total error E_t is computed in the following equation:

$$E_t = \frac{1}{2m}\sum_{k=1}^{m} E_k \tag{4}$$

Define $\lambda_{jk}^{l} = \left(\partial E_k / \partial p_{jk}^{l}\right)$, then

$$\frac{\partial E_k}{\partial w_{ij}^{l}} = \frac{\partial E_k}{\partial p_{jk}^{l}}\frac{\partial p_{jk}^{l}}{\partial w_{ij}^{l}} = \frac{\partial E_k}{\partial p_{jk}^{l}} o_{jk}^{l-1} = \lambda_{jk}^{l} o_{jk}^{l-1} \tag{5}$$

If unit j is the last output unit, $o_{jk}^{l} = y'_{jk}$. With Eq. (3), then

$$\lambda_{jk}^{l} = \frac{\partial E_k}{\partial p_{jk}^{l}} = \frac{\partial E_k}{\partial y'_{jk}}\frac{\partial y'_{jk}}{\partial p_{jk}^{l}} = -\left(y_k - y'_k\right) f'\left(p_{jk}^{l}\right) \tag{6}$$

And if unit j is not the last output unit, then

$$\lambda_{jk}^{l} = \frac{\partial E_k}{\partial p_{jk}^{l}} = \frac{\partial E_k}{\partial o_{jk}^{l}}\frac{\partial o_{jk}^{l}}{\partial p_{jk}^{l}} = \frac{\partial E_k}{\partial o_{jk}^{l}} f'\left(p_{jk}^{l}\right) \tag{7}$$

where o_{jk}^{l} is the input of layer $l+1$, and $\left(\partial E_k / \partial o_{jk}^{l}\right)$ can be calculated on the layer $l+1$.

For unit m of layer $l+1$, Eq. (8) is given.

$$\frac{\partial E_k}{\partial o_{jk}^{l}} = \sum_{m}\frac{\partial E_k}{\partial p_{mk}^{l+1}}\frac{\partial p_{mk}^{l+1}}{\partial o_{jk}^{l}} = \sum_{m}\frac{\partial E_k}{\partial p_{mk}^{l+1}} w_{mj}^{l+1} = \sum_{m}\lambda_{mk}^{l+1} w_{mj}^{l+1} \tag{8}$$

Substituting Eq. (8) into Eq. (7) and (9) is obtained.

$$\lambda_{jk}^{l} = \sum_{m}\lambda_{mk}^{l+1} w_{mj}^{l+1} f'\left(p_{jk}^{l}\right) \tag{9}$$

To sum up, the BP neural network algorithm is implemented as following procedures. The first, determine initial values of weight coefficients. The second, o_{jk}^{l-1}, p_{jk}^{l} and y'_k for forward propagation are computed, while $k = 2, \ldots, m$. And λ_{jk}^{l} is calculated for back propagation from the layer $l-1$ to layer 2. Then the weight coefficient is corrected in the following equation:

$$w_{ij} = w_{ij} - \eta\frac{\partial E}{\partial w_{ij}}, \quad \eta > 0 \tag{10}$$

Above steps repeat until the total error $E_t < \varsigma$, where ς is the specified precision.

3. Methodologies analysis

In literature [20], the least-square-based approach is proposed. The least square method is a widely used mathematic optimization method for data processing, which seeks for the best matching function for processed data via minimizing the sum of the squares of the errors. Then un-sampled data could be calculated with the least square method. Compared with the data for static experiments in the lab in [20], for dynamic laser ranging, the linearity of experiment data would be worse. BP neural network, the basic structure