PSO-based integration navigation and LiDAR-based remote sensing algorithms for 3D agriculture digital modeling with light multi-rotor UAV

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1. Introduction

LiDAR is a promising active remote sensing technology that has been applied in many scientific fields to extract key parameters of biophysics [1–3]. As one of the most effective active remote sensing technologies, LiDAR has great advantages in obtaining the target physical parameters [4]. Airborne laser scanner (ALS) and terrestrial laser scanner are the two most common platforms of LiDAR [5]. The data obtained by LiDAR remote sensing can achieve better observation of individual plants, which is unmatched by the traditional two-dimensional data obtained by images [6–9]. LiDAR has been widely used in many fields. LiDAR can provide information about the horizontal and vertical structure of the forest and has been successfully used to estimate the height of the canopy [10–12]. There are also many research results for the establishment of laser radar three-dimensional digital model and target extraction. Alexander et al. [13] studied the effect of slope and canopy...
characteristics on treetop and tree height estimation of ALS data for complex terrain and complex canopy characteristics in forests. The same method using the digital surface model minus the digital terrain model to derive the canopy height model can be used as a reference for estimating the plant height on the canal slope. He et al. [14] used multiple 2D laser radars to establish a 3D environment, so calibrating the geometric transformation between multiple sensors and carrier frames is a research focus. This study proposes a method that can calibrate multiple 2D laser radars, a calibration algorithm based on multi-type geometric features is proposed, which is to extract features such as points, lines, surfaces and quadrics from the point cloud data of each LiDAR sensor to achieve matching of multiple radar data. The segmentation method of building top surface area growth of the building with the laser radar point cloud data is constructed. The segmentation of the top surface of the building can be accurately realized. Because the intensity information of point cloud has certain separability, the classification of ground materials can be realized [15]. Cao et al. [16] aimed to associate the active remote sensing with the passive remote sensing to retrieve the forest canopy cover using the linear spectrum decomposition model and geo-optical model, which makes forest canopy coverage easier to retrieve. Fayad et al. [17], Wang et al. [18], Xiang et al. [19], Paris and Bruzzone [20] studied the application of LiDAR remote sensing data in forest canopy detection and single-wood detection, including point cloud difference and filtering. However, current airborne and satellite LiDAR systems are unable to provide data on a regional and global scale. The unmanned aerial vehicle (UAV) is highly flexible and the UAV-equipped LiDAR remote sensing system can quickly and simultaneously collect data from the same area. The airborne LiDAR system consists of two parts: LiDAR and integrated navigation system. In order to improve the accuracy of remote sensing operations, the optimization of the algorithm can further improve the accuracy when the hardware cannot be improved. For the past several decades, there has been a great change in integrated navigation systems. In order to exploit the complementary characteristics of different sensors, different navigation sensors were combined [21,22]. However, the global position system/inertial navigation system (GPS/INS) integrated navigation system is still the most sophisticated navigation system, which has been widely used to provide the geographical position, velocity, and attitude of a vehicle. Traditional GPS/INS integrated systems can bridge the GPS gaps and the navigation capability is strongly dependent on the performances of stand-alone INS [23]. The GPS/INS integration system is designed by employing an adaptive filter that can estimate measurement noise variance using the residual of the measurement [24]. Ultra-tightly coupled method is the best but it is too complicated [25–27]. In Wang et al. [28], a combined navigation method for small agricultural drones is proposed. The feedback correction method is used in the paper. Finally, the experimental results show that the filtered navigation parameter error is reduced before filtering. Yadav et al. [29] clarifies about the advancement of GPS and INS models and demonstrate in getting the exact values in all aspects. Zhou et al. [30], Derbel et al. [31], Oh and Hwang [32], Chen [33], Choi et al. [34], Liu et al. [35] has improved the integrated navigation method to varying degrees. The particle swarm optimization (PSO) has received increased attention in many research fields in recent years [36]. PSO was first proposed by Eberhart and Kennedy [37]. PSO is a simple and effective optimization algorithm that can achieve fast convergence by adjusting parameters [38–40]. Cai et al. [41], Li et al. [42], Liu [43], Qu et al. [44] have developed a variety of applications and developments in PSO. This paper is dedicated to promoting the application of LiDAR remote sensing methods in agriculture and canal irrigation is the top priority of agricultural production. The ecological irrigation canal is the main content of the construction of water-saving and ecological irrigation areas, which is an important link in the process of building modern agriculture. The water canal was built in the 1950s for irrigation to maintain local agriculture during the dry season [45]. The construction of ecological irrigation canals plays an important role in improving the modern environment and alleviating the shortage of water resources. Therefore, the construction of ecological irrigation canals is the only way for the development of China’s agricultural modernization. Agricultural water use efficiency has been affected by farming methods, fertilization methods, and irrigation schedules, which is also affected by the construction of farmland water conservancy infrastructure [46–48]. Because of the unstable precipitation in arid and semi-arid regions, irrigation channels are important for food and food supplies in these areas [49,50]. From the aspect of technical efficiency, the efficiency of water allocation can be improved through water circulation and irrigation [51,52]. Therefore, the construction of ecological irrigation canals is the only way for the development of China’s agricultural modernization. At the same time, the efficiency of agricultural water can be increased.

The aim of this paper is to develop and apply an approach that realizes the extraction of ecological irrigation areas and the establishment of a three-digit model of ground crops. Through these efforts, we will lay the foundation for the establishment of a three-dimensional digital model of ecological irrigation channels and crops in the future and thereby promote the digitization of agricultural production. The other sections are arranged as follows: section 2 – Global Navigation Satellite System/Inertial Navigation System (GNSS/INS) integrated navigation system model is built, the PSO algorithm was introduced; In section 3, Point cloud data acquisition was introduced; section 4, the feature extraction algorithm was introduced; section 5 is experiment and verification, the validity of the PSO algorithm is verified and the model of ecological irrigation canal and three ground groups were established, the reasons for the test error are also discussed in detail.

2. GNSS/INS integrated navigation system

2.1. GNSS and INS error model

The coordinate system of INS adopts the “geographical coordinates of East-North-Up (ENU)”. The navigation information error is nine-dimensional, including the three-dimensional platform error angle $\phi_p$, $\psi_p$, $\varphi_p$, the three-dimensional
speed error \( \delta v_x, \delta v_y, \delta v_z \) and the three-dimensional position error \( \delta \lambda, \delta \varphi, \delta h \). The earth’s rotation angular velocity is \( \omega_x \). The ellipsoidal equatorial plane radius \( R_e = 6,378,137 \) m, radius of curvature in prime vertical \( R_N = R_e(1 - \varepsilon \sin^2 \varepsilon \) m), radius of meridional section \( R_M = R_x(1 - 2f + 3f^2 \sin^2 \varepsilon \) m). Ovality is \( f = 1/298.257 \)  

The location \( S_{\text{eq}} \) is deduced as follow:  
\[
\begin{align*}
X &= X_I + X_{G} \\
Y &= Y_I + Y_{G} \\
Z &= Z_I + Z_{G} \\
\end{align*}
\]

2.2. GNSS/INS integrated navigation system model

The corresponding equation of state is given by  
\[
\dot{X} = Fx + Gw
\]  
(8)

where \( X = [X_I, X_G]^T \) is state variable,  
\[
F = \begin{bmatrix} \frac{d}{dt} & 0 \\ 0 & F_G \end{bmatrix}
\]

is transition matrix,  
\[
G = \begin{bmatrix} G_1 & 0 \\ 0 & G_G \end{bmatrix}
\]

is dynamic noise matrix,  
\[
w = [w_x, w_y]^T
\]

is the process white noise matrix of the system, the subscript “I” and “G” represent INS and GNSS.

In this paper, the speed difference and the position difference are chosen as the external observations to establish the combined measuring equations of position and velocity.

\[
\begin{align*}
L_{\text{INS}} &= \begin{bmatrix} L_{i} - N_{i} \\
\lambda_{i} - \delta \lambda \\
h_{i} - \delta h \end{bmatrix} \\
L_{\text{GPS}} &= \begin{bmatrix} \frac{L_{i} - N_{i}}{R} \\
\frac{\lambda_{i} - N_{i}}{R \cos L} \\
h_{i} - N_{i} \end{bmatrix} \\
\end{align*}
\]

(9)

(10)

where \( L_{\text{INS}}, \lambda_{\text{INS}}, h_{\text{INS}} \) and \( L_{\text{GPS}}, \lambda_{\text{GPS}}, h_{\text{GPS}} \) represent the longitude, latitude and altitude calculated by the INS, \( L_{i}, \lambda_{i}, h_{i} \) represent the carrier’s true longitude, latitude and altitude information, \( \delta L, \delta \lambda, \delta h \) represent the longitude error, latitude error and height error solved by INS.

2.3. Combined equation of state

Because the carrier is stationary, in the GPS receiver data acquisition interval, the speed as a constant value, so only consider the horizontal direction. The error model of GPS selects four-dimensional state model:

\[
X_{G} = \begin{bmatrix} \delta v_x, \delta v_y, \delta v_z, \delta \lambda \end{bmatrix}^T
\]

(6)

\[
A_{G} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \frac{1}{R_M + h} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}
\]

(7)

where the earth radius is \( R_M = R_e(1 - 2f + 3f^2 \sin^2 \varepsilon \) m), \( R_N = R_x(1 + \varepsilon \sin^2 \varepsilon \) m), \( f = 1/298.257 \).
where \( M_x, M_y, M_z \) are the components of the velocity measurement errors on the three axes of East-North-Up. The velocity error of the external measurement can be defined as \( Z_{vel} = \begin{bmatrix} v_{INS} - v_{GPS} \\ v_{INS} - v_{GPS} \\ v_{INS} - v_{GPS} \end{bmatrix} \). The velocity measurement equation is given by:

\[
Z_{vel} = H_{vel}(t)X(t) + V_{vel}(t)
\]

According to Eqs. (9)–(14), we can get a GNSS/INS integrated navigation system’s position and velocity combination measurement equation:

\[
Z(t) = \begin{bmatrix} \lambda_{INS} - \lambda_{GPS} \\ \lambda_{INS} - \lambda_{INS} \\ v_{dps} - v_{gps} \\ v_{dps} - v_{gps} \\ v_{dps} - v_{dps} \end{bmatrix} = H(t)X(t) + V(t)
\]

2.3. GNSS/INS integrated navigation information fusion framework

In this paper, centralized Kalman filtering is used to process INS and GNSS data. INS and GNSS data are sent to the same Kalman filter. When the state vector in the filtering equation is a combination of the error state of the INS navigation parameter and the error state of the GPS navigation parameter as follow:

\[
\Delta X = \Delta X_s + \Delta X_G
\]

Then the Kalman filter’s optimal error estimation \( \left( \Delta \hat{X}_s, \Delta \hat{X}_G \right) \) can correct the original system to obtain accurate navigation parameters. In this paper, the discrete Kalman filter algorithm is introduced to estimate the state estimation of the next moment according to the system state estimation of the previous moment through the recursive algorithm. The system does not need to store a large amount of measured data. The estimation process is shown by the following five equations:

- **State one-step prediction**:
  \[
  \hat{X}_{s(k|k-1)} = \Phi_{s(k|k-1)} \hat{X}_{s(k-1)}
  \]

- **Predict the mean square error**:
  \[
  P_{s(k|k-1)} = \Phi_{s(k|k-1)} P_{s(k|k-1)} + \Gamma_{s(k|k-1)} \Gamma_{s(k|k-1)}
  \]

- **Filter gain**:
  \[
  K_k = P_{s(k|k-1)} H_{s(k|k-1)}^T \left( H_{s(k|k-1)} P_{s(k|k-1)} H_{s(k|k-1)}^T + R_k \right)^{-1}
  \]

- **Optimal state estimation**:
  \[
  \hat{X}_s = \hat{X}_{s(k|k-1)} + K_k \left( Z_k - H_{s(k|k-1)} \hat{X}_{s(k|k-1)} \right)
  \]

- **Estimate the mean square error**:
  \[
  P_k = (I - K_k H_{s(k)}) P_{s(k|k-1)}
  \]

where \( Q \) is system noise covariance matrix, \( R \) is measurement noise covariance matrix, \( H_{s(k)} \) is the one-step transfer matrix from the time instant \( t_{k-1} \) to time instant \( t_k \). \( H_k \) is measurement array, \( V_k \) is measurement noise sequence. Given the initial value \( \hat{X}_0 \) and \( P_0 \), according to the \( k \) moment of measurement \( Z_k \), the state estimations \( \hat{X}_k \) \((k = 1, 2, 3 \ldots)\) can be recursive calculated by the measurement \( Z_k \) of the \( k \)th moment.

2.4. PSO algorithm

Assume that in the D-dimensional search space, a population of \( n \) particles \( X = (X_1, X_2, \ldots, X_n) \), where the \( i \)-th particle is represented as a D-dimensional vector \( X_i = (X_{i1}, X_{i2}, \ldots, X_{iD}) \), representing the position of the \( i \)-th particle in the D-dimensional search space and a potential solution to the problem. According to the objective function, the fitness value corresponding to each particle position \( X_i \) can be calculated. The velocity of the \( i \)-th particle is \( V_i = (V_{i1}, V_{i2}, \ldots, V_{iD}) \) and the population extremum of the population is \( P = (P_{1}, P_{2}, \ldots, P_{n}) \). During each iteration, the particles update their speed and position through individual extremum and population extremum. The formula is as follows:

\[
V_i(t + 1) = w V_i(t) + c_1 r_1 \left[ P_{best} - x_i(t) \right] + c_2 r_2 \left[ G_{best} - x_i(t) \right]
\]

\[
x_i(t + 1) = x_i(t) + V_i(t + 1)
\]

where \( V_i \) and \( x_i \) are the velocity and position of particle \( i \) in the \( j \)-th dimension respectively; \( P \) best is the individual optimal position of the space search after particle \( i \) traversal; \( G_{best} \) is the global optimal position of all particles searched so far; \( t \) represents the current time; \( c_1 \) and \( c_2 \) are non-negative constants called acceleration factors; \( r_1 \) and \( r_2 \) are random numbers distributed in the interval \((0,1)\).

In this paper, the fitness function is as follow:

\[
S = \text{Var}(X_{\text{L}}) + \text{Var}(X_{\text{L}}) + \text{Var}(X_{\text{V}}) + \text{Var}(X_{\text{W}})
\]

where \( X_{\text{L}} \) is the longitude error, \( X_{\text{L}} \) is the latitude error, \( X_{\text{V}} \) is the eastward velocity error, \( X_{\text{W}} \) is the northward velocity error.

3. Point cloud data obtain and processing

Establishing accurate models of ground objects can play an important role in urban design planning, agricultural
production, and water conservancy construction. The modeling process of low-altitude remote sensing, oblique photogrammetry, and LiDAR-based 3D modeling is given in Fig. 1. All three methods can generate three-dimensional models of targets, but methods (a) and (b) use passive sensing devices to obtain image data, which is greatly affected by the intensity of light. The LiDAR used in the method (c) belongs to the active remote sensing device, which can still work normally under the meteorological conditions and nighttime when the light is weak. In addition, multi-image matching is a key step in the method (a) and (b) operation. The goal of establishing a three-dimensional model in this paper is mainly for crops and irrigation canals in ecological irrigation districts. The modeling results of methods (a) and (b) are severely affected when the model object is a large area of wheat. Because the background color is all green, the matching of the correspondence points will cause a large error due to the inability to find an obvious reference. In addition, the problem of precision control needs to be considered, and methods (a) and (b) do not perform well in the measurement of elevation accuracy, so more production time and cost are required in order to improve the elevation precision. Method (c) can directly generate a target point cloud with no requirements for the color and background of the target. It reduces the requirements of the operating environment and saves a lot of production time.

3.1. Coordinate transformation

After obtaining the distance R between the laser transmitting point and the target point, it is necessary to obtain the three-dimensional space coordinates in the World Geodetic System-1984 Coordinate System (WGS-84) through the transformation of multiple coordinate systems. Therefore, in the laser beam coordinate system, the laser foot point can be expressed as:

\[
\begin{bmatrix}
\dot{x}_{lp} \\
\dot{y}_{lp} \\
\dot{z}_{lp}
\end{bmatrix} = \begin{bmatrix}
0 \\
0 \\
R
\end{bmatrix}
\]  

(25)

In the laser scanning coordinate system, the laser foot point can be expressed as:

\[
\begin{bmatrix}
\dot{x}_p \\
\dot{y}_p \\
\dot{z}_p
\end{bmatrix} = \begin{bmatrix}
1 & 0 & 0 \\
0 & \cos \theta_i & -\sin \theta_i \\
0 & \sin \theta_i & \cos \theta_i
\end{bmatrix} \begin{bmatrix}
0 \\
0 \\
R
\end{bmatrix}
\]  

(26)

where \( \theta \) is the instantaneous scanning angle of the laser beam, which is mainly calculated by the number of system scanning angle \( \theta \) and system scanning angle \( N \), then the calculation formula of the number of \( i \) instantaneous scanning angle is:

\[
\theta = \frac{\theta - i \times \frac{\theta}{N - 1}}{2}
\]  

(27)

In the airborne LiDAR system, the scanning device and INS of LiDAR must have certain angle errors in installation, so their coordinate systems can’t be guaranteed to be parallel. We suppose that the angle between the two coordinate systems and the three coordinate axes is \( \alpha, \beta, \gamma \) and the offset between the origin of the two coordinates is \( (\Delta x_i, \Delta y_i, \Delta z_i)^T \). Therefore, the laser foot point is expressed in the inertial navigation platform coordinate system as follows:

\[
\begin{bmatrix}
X_i \\
Y_i \\
Z_i
\end{bmatrix} = R_i \times \begin{bmatrix}
X_p \\
Y_p \\
Z_p + \Delta x_i
\end{bmatrix}
\]  

(28)

Fig. 1. (a) Low-altitude remote sensing, (b) oblique photogrammetry, and (c) LiDAR-based 3D modelling.
where \( R_i \) is the transformation matrix, among them:

\[
\begin{bmatrix}
1 & 0 & 0 \\
0 & \cos\alpha & -\sin\alpha \\
0 & \sin\alpha & \cos\alpha
\end{bmatrix},
\begin{bmatrix}
\cos\beta & 0 & \sin\beta \\
0 & 1 & 0 \\
-\sin\beta & 0 & \cos\beta
\end{bmatrix}
\]

\[
R(\alpha) = \begin{bmatrix}
1 & 0 & 0 \\
0 & \cos\phi & -\sin\phi \\
0 & \sin\phi & \cos\phi
\end{bmatrix},
R(\beta) = \begin{bmatrix}
\cos\gamma & 0 & \sin\gamma \\
0 & 1 & 0 \\
-\sin\gamma & 0 & \cos\gamma
\end{bmatrix}
\]

The position of the error caused by the interpolation of a regular lattice net is reduced. It’s also structurally quite simple. The position of each point can be calculated by the following formula:

\[
\begin{align*}
X_{id} &= \frac{X_{i} \cdot X_{\text{min}}}{\text{cellsize}} \\
Y_{id} &= \frac{Y_{i} \cdot Y_{\text{min}}}{\text{cellsize}}
\end{align*}
\]

where \( X_{i}, Y_{i} \) are the coordinates of a point, \( X_{\text{min}}, Y_{\text{min}} \) is the minimum in the \( X, Y \) direction, cell size is the edge length of the partition grid.

Mathematical morphological filtering methods include open and close operations, the two algorithms are composed of basic operations of expansion and corrosion. When processing point cloud data, the maximum elevation value of point cloud in the filtering window will be selected as the new elevation value of the point. The formula is as follows:

\[
[\delta_{i}(f)](x, y) = \max \left\{ f(x+i, y+j) \mid i, j \in [-w, w], (x+i, (y+i) \in D_{i}] \right\}
\]

The corrosion operation is to select the minimum elevation value of the point cloud in the filtering window as the new elevation value of the point. The formula is as follows:

\[
[e_{i}(f)](x, y) = \min \left\{ f(x+i, y+j) \mid i, j \in [-w, w], (x+i, (y+i) \in D_{i}] \right\}
\]

The first operation is corrosion and then expansion. The closed operation is opposite, the formula is as follows:

\[
[\gamma_{i}(f)] = [e_{i}(f)]
\]

\[
[\beta_{i}(f)] = [\delta_{i}(f)]
\]

The method of opening operation is generally used to acquire 3D point cloud data on the ground, that is, to remove the non-ground 3D point cloud data. Using Eq. (36) to calculate the difference between the elevation value of the original point cloud data and the elevation value after opening operation and then compare the difference with the
filtering threshold $T$. If it is greater than $T$, remove the point, otherwise remain.

$$dH = f - \delta_0 \left[ e_0(f) \right]$$

(36)

The flow chart of point cloud data processing in the target area is shown in Fig. 2.

4. Feature extraction

After obtaining the point cloud data of the ecological irrigation canal area, it is necessary to extract its characteristic lines. The method of extracting the characteristic line of the point cloud of the building is suitable for the extraction of the intersection line of the surface and the surface. The same characteristic line exists in the ecological irrigation canal. Therefore, the point cloud data of the ecological irrigation canal area are processed in section 3. The $k$-dimensional (K-D) tree [53] is used to search the local $K$-neighborhood of point $N_{p_j} = \{(x, y, z) \in R^3 | j = 1, 2, 3...k\}$ and find out the Euclidean distance of current point $P_j$ and it can be shown as follow:

$$\text{dist} = \sqrt{(x - x_j)^2 + (y - y_j)^2 + (z - z_j)^2} \ (x, y, z, z_j) \in N_{p_j}$$

(37)

Sort the selected $k$ points by distance from large to small and take the current point as a vertex. As shown in Fig. 3, the three-neighbourhood points A, B, C constitute a plane triangle. Calculate the distance from $p_i$ to triangle ABC. The point $d_j$ on the characteristic line is larger, the point $d_j$ on the ground and slope is smaller. In order to reduce the noise influence on the extraction of characteristic line, the average value of $d_j$ is compared to the set threshold $d_{\text{min}}$ and if the average value $d$ is greater than the set threshold, then the point remains.

Most sections of ecological irrigation canals are inverted trapezoidal or rectangular. Taking the inverted trapezoidal section as an example, the characteristic line schematic diagram is shown in Fig. 4.

However, unlike the extraction of the characteristic lines of a building, the ecological irrigation canal is rougher than the wall surface of the building and there is an influence of debris such as stones and weeds.

Therefore, the set threshold must be accurate, otherwise, it will cause a greater error. In this paper, the first calculation of the ecological irrigation canal characteristics line is the ecological irrigation area slope $d_j$ then take the average $d_j$ as the set threshold $d_{\text{min}}$ and compare with $d$. This way avoids deleting points on the true feature line because the selected $d_{\text{min}}$ is small when the surface of the ecological irrigation canal slope is rough and there is a lot of debris.

5. Experiment and verification

5.1. PSO experiment

We use a joint optimization method for the system noise variance matrix $Q$ and the measurement noise matrix $R$. When performing the PSO algorithm, we set the number of iterations to 30, 50, and 100 times. There are 12 parameters for optimizing $Q$ and $R$, and the range of values we set in this paper is as follows: The upper limit of the values of and is $0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05$ and $0.05$. The lower limit of the values of and is $0.00001, 0.00001, 0.00001, 0.00025, 0.00225, 0.002, 0.0001, 0.001, 0.0001, 0.02, 0.2, 0.2, 0.2, 0.2$. 

Fig. 2. Point cloud data processing.

Fig. 3. Feature point and plane triangle schematic.

Fig. 4. Ecological irrigation canal section and characteristic line.
When the number of iterations is 30, 50, and 100 times, the iteration convergence curve, longitude, and latitude error curve are shown in Fig. 5. Figs. 5a–c and Table 1 show that the error parameters of longitude and latitude are greatly reduced when the number of iterations is 30 times. The variance of PSO-filtered error of longitude error is 0.00086, the variance of PSO-filtered error of latitude error is 0.00059, the optimal objective function value is 1.0614. But the iterative convergence curve shows that the number of iterations is 30 times, the curve does not completely converge, so the number of iterations must be increased. When the number of iterations is 50 times, Figs. 5d–f and Table 1 show that the error of the latitude and longitude error phase is further reduced. The variance of PSO-filtered error of Longitude error is 0.00077, the variance of PSO-filtered error of latitude error is 0.0004, the optimal objective function value is 0.84712. The convergence characteristic curve has converged, but to prevent the optimization from falling into local optimum, the number of iterations is increased to 100 times. Figs. 5g–i and Table 1 show that the number of iterations is 100 times, the variance of PSO-filtered error of longitude error is 0.00076, the variance of PSO-filtered error of latitude error is 0.00041, the optimal objective function value is 0.84906. The above chart shows that after the optimization curve enters the global optimum at the 38th iteration, the iteration still converges at the same position when the number of iterations is 100, and the longitude error and the latitude error have no significant change compared with 50 times, which indicates that the optimization result is the optimal state.

5.2. 3D model generation of ground crops

In order to verify the effectiveness of this algorithm, as shown in Fig. 6, we use RPLIDAR A2 and fix it on the UAV to collect data, the GPS module and the IMU are also installed. The parameters of the Lidar are shown in Table 2.

The data output from LiDAR system includes Chiptime, $a_x(g)$, $a_y(g)$, $a_z(g)$, $w$(deg/S), $w$(deg/S), $w$(deg/S), angle (deg), angle_x(deg), angle_y(deg), angle_z(deg), Lon(deg), Lat(deg). Herein,
Chiptime is the timestamp corresponding to the collected data. \( a_x(g), a_y(g), a_z(g) \) is the acceleration of the current carrier along each of the three axes. \( w_x(\text{deg}/S), w_y(\text{deg}/S), w_z(\text{deg}/S) \) is the angular velocity of the three axes of the current carrier. Angle (deg), angle (deg), angle (deg) is the roll, pitch and yaw attitude angle. Lon(deg), Lat(deg) is longitude and latitude. Airborne LiDAR system can collect point cloud data and longitude and latitude information at the same time. We selected three representative ground crops in the agricultural irrigation area as the target of this experiment.

Wheat represents the most widely grown food crop, and \( Euonymus \) \( japonicus \) and \( Anemone \) have both medicinal value and ornamental value. The three ground groups are shown in Figs. 7a, c, e and g. The three-dimensional digital model is shown in Figs. 6b, d, f and h.

The experiments are run on the MATLAB 2017 (a) platform. As shown in Fig. 7, the direction of the red arrow is the direction of the UAV flight. The height of UAV from the ground target is set at 5 m. According to the point cloud data obtained in section 3, we obtained point cloud data for the target crop. MATLAB is used to build a three-dimensional digital model of the target crop. As shown in Fig. 7, the 3D model of the wheat, \( Euonymus \) \( japonicus \) and \( Anemone \) were built. The error between the 3D model and the actual crop average height data is compared in Table 3. In order to detect the accuracy of generating a three-dimensional model, the average height of each ground crop is calculated by taking a certain number of sampling points on the surface of the crop. As shown in Table 3, the average height of wheat is 712.63 and 526.306 mm, the 3D model average height of wheat is 678.58 and 502.832 mm, the average height of \( Euonymus \) \( japonicus \) is 920.33 mm, the 3D model average height of the sedum \( Euonymus \) \( japonicus \) is 867.65 mm. The average height of the \( Anemone \) is 410 mm, the 3D model average height of the \( Anemone \) is 440 mm.

5.3. Ecological irrigation canal extraction

In order to verify the extraction method of the ecological irrigation canal characteristic line proposed in this paper, we also selected an ecological irrigation canal for data collection in the Hetao irrigation area of Inner Mongolia. The ecological irrigation canal and the three-dimensional digital model of the ecological irrigation canal are shown in Fig. 8 at different angles and the characteristic lines are obvious.

As shown in Table 4, the errors between the actual value and the 3D model in average depth and height are 4.42% and 4.66%.
Fig. 7. The ground group (a) wheat in grouting period, (b) wheat in the jointing stage, (c) *Euonymus japonicus*, (g) *Anemone*, (b, d, f and h) are three-dimensional digital models corresponding to ground crops.
4.56%. The 3D model can reflect the shape and size of real ecological irrigation canals. The experiment proves that the airborne LiDAR point cloud data acquisition system works well. The ecological irrigation canal extraction algorithm proposed in this article is effective.

5.4. Discussion

In this section, a LiDAR remote sensing data acquisition system based on light multi-rotor UAV is established to collect point cloud data of ground targets. The linear decreasing PSO experiments, three-dimensional digital model generation of ground crops and extraction of ecological irrigation canals are carried out separately. The method of MATLAB simulation is used to verify that the Kalman filtering algorithm optimized by linear decreasing PSO can reduce the positioning error of the integrated navigation system. The three-dimensional digital model of surface crops and ecological irrigation canals are established. The error between the actual target and 3D model mainly comes from the following two aspects after analysis: (1) LiDAR ranging error, the LiDAR used in this paper has an error is +/-4 cm at the distance of 10 meters. (2) The mounting position error between the LiDAR and the inertial navigation sensor is preserved with the matrix transformation of the point cloud data.

6. Conclusions

Further increasing the application of advanced sensors such as LiDAR in agricultural production meets the requirements of current digital agricultural development. In traditional mapping operations, the camera is heavily influenced by weather and lighting factors, which greatly increases the difficulty of post-processing. The remote sensing methods of fixed-wing aircraft and satellite-equipped LiDAR are costly and have low real-time performance. The linear descending PSO algorithm is used to improve the positioning accuracy of multi-rotor UAV remote sensing. Experiments show that the linear decreasing PSO algorithm can greatly improve the latitude and longitude output accuracy and help to improve the positioning accuracy of the airborne LiDAR remote sensing system. Through filtering and
interpolation of point clouds, three representative surface crops in the agricultural irrigation area were successfully established. Rapid detection of crop growth height could be achieved by data derived from a three-dimensional model. By extracting the characteristic line of the ecological irrigation canal, the extraction of the ecological irrigation canal is realized and the three-dimensional digital model of irrigation canal is established. The distribution of ecological irrigation canals in agricultural irrigation areas can be accurately controlled by the irrigation canal digital model. The irrigation canal size derived from the irrigation canal digital model can calculate the water transfer capacity of irrigation canals. Through the above two aspects, the supply and demand analysis and rational distribution of water resources in the whole agricultural irrigation area can be realized, which meets the needs of precision agriculture and digital agriculture. The limitation of this paper is that only the extraction experiment of the irrigation canal in a specific area is carried out. In the future, LiDAR remote sensing will be more widely used in the extraction of ecological irrigation canals and the reconstruction of crop 3D digital models. Moreover, owing to the flexibility of a multi-rotor UAV in remote sensing operations in specific areas, a multi-rotor UAV equipped with a small LiDAR or optical image remote sensing system will be more suitable for remote sensing operations in the agricultural field [54,55].

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