A Novel Simultaneous Calibration and Localization Algorithm Framework for Indoor Scenarios

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ABSTRACT Under the navigational process of simultaneous beacon-calibrating and target-positioning, the real-time positioning and calibrating accuracy in indoor scenarios is significantly limited. To solve it, a novel Simultaneous Calibration and Localization (SCAL) algorithm framework for indoor scenarios is proposed. The proposed framework is mainly divided into the Target Localization and Beacon Calibration (TLBC) and the Global Optimization (GO) section: in the TLBC section, under the typical distributed beacon layout, a processing mechanism for synchronously locating the target and calibrating beacons is proposed; in GO section, parallel to TLBC section, a global optimization method based on Geometric Dilution of Precision based on Error-propagation (EGDOP) model is further proposed, and it can utilize the geometric trajectory of target and positioning error of target and beacons to efficiently and simultaneously optimize the positioning of target trajectory and beacons from TLBC section. The numerical simulation results show that the improvement of the GO section on the positioning performance is verified. Compared with the SCAL algorithm based on backward processing with inverse trajectory, the proposed framework has improved the accuracy of target and beacon positioning by 39.06% and 58.01%, respectively, and accuracy of positioning reaches 0.2557m and 0.2437m, respectively, in an actual indoor positioning scene.

INDEX TERMS Simultaneous calibration and localization, indoor localization, global optimization, EGDOP.

I. INTRODUCTION

Nowadays, with the coming of the Internet of Everything era, people’s demand for high-precision indoor position increases significantly [1], [4]. Due to the high reliability, precision, portability and low cost of positioning technologies based on wireless signals (e.g. Wi-Fi [5], Ultra-Wide Band (UWB) [6], Bluetooth [7], etc.), it is widely used in indoor.

High-precision of positioning technology based on wireless signals is premised on the accurate calibration of beacons. Therefore, in high-precision positioning research based on wireless signals, accurate calibration of beacons is also an important research hotspot. At present, there are two main ways to obtain the position of beacon: offline and online calibration. The offline calibration method must obtain the position of the beacon using specific instruments such as Total Station [8] before the positioning system runs. In general, the offline calibration method has high accuracy in estimating the position of the beacon, but generally requires considerable time and acquisition cost, which makes it not suitable for large positioning scenarios with a large number of beacons. Additionally, the position acquisition of a beacon needs to be performed in advance, so it is difficult to quickly configure the positioning system in an unfamiliar environment.

The online calibration method mainly includes the distributed positioning method and Simultaneous Calibration and Localization (SCAL) method. In the distributed positioning method each node in the distributed network realizes its localization by interacting with the observation information of neighboring nodes. In [9] a distributed positioning algorithm based on particle filtering and a bi-directional communication network for UWB nodes was proposed, which can reach 1m-level positioning accuracy with several targets’ interaction. The distributed positioning method can locate
The paper is organized as follows: Section II gives the system model of this article. Section III demonstrates an overview of the proposed algorithm framework. The TLBC section and GO section are illustrated in Section IV and Section V. Then simulations in Section VI and experiments in Section VII are designed to evaluate the performance of the proposed SCAL algorithm framework. Section VIII gives the conclusions of this article.

II. SYSTEM MODEL
To ensure the applicability of the following discussion, the basic principle of beacon layout is: when the target with a signal receptor is moving, not less than 4 beacons are observed, which includes not less than 3 observable beacons with initially globally-known positions at the start and end of target trajectory.

For the convenience of the following discussion, one of the suitable deployment of beacons is selected for the following discussion: there is an indoor scenario that has the entrance and exit; there are 6 Beacons with Globally-known Position (GP Beacon) with 3 of them placed at entrance and exit, respectively; there are several Beacons with Unknown Position (UP Beacon); target moves within the cubic space composed by beacon system, and the whole three-dimensional diagram is as Fig.1:

![FIGURE 1. Schematic diagram of beacons distribution (red five-pointed stars represent GP beacons and blue six-pointed stars represent UP beacons).](image)

The proposed SCAL algorithm framework is based on the ranging method (e.g. Wi-Fi, UWB, Bluetooth, etc.) between the target and beacons. The typical ranging observation equation is:

\[ d = \sqrt{(x_B - x_r)^2 + (y_B - y_r)^2 + (z_B - z_r)^2 + \varepsilon} \]  

(1)

where \( d \) represents the ranging from beacon to target; \([x_B, y_B, z_B]\) and \([x_r, y_r, z_r]\) represents the position of the beacon and target respectively; \( \varepsilon \) represents ranging noise.

For the feasibility of the proposed algorithm, at least 4 beacons need to be observed at any time within the target observing range, and its two-dimensional diagram is as in Fig.2:

![FIGURE 2. Two-dimensional diagram of the geometric relationship of beacon distribution.](image)
As the geometric relationship of Fig.2, the relative distance distribution between any adjacent two beacons should fit:

\[ d_x^2 + d_y^2 + 4d_z^2 \leq R_{UB}^2 \]  

where \( R_{UB} \) is the semi-diameter of beacon signal coverage; \( d_x, d_y, d_z \) are distances between any adjacent beacons respectively on the X, Y, and Z axis.

### III. OVERVIEW

The proposed algorithm framework is divided into two parts: the Target Localization and Beacon Calibration (TLBC) section (inside the dashed box of Fig.3) and the Global Optimization (GO) section (outside the dashed box of Fig.3).

In the TLBC section, as in Fig.3, target positioning based on GP beacon observations and UP beacon calibration based on target trajectories is synchronously performed. And UP beacon can be converted into GP beacon to provide beacon locations for subsequent target positioning.

In the GO section parallel to the TLBC section as in Fig.3, the target trajectory is screened based on the EGDOP model, and then the position of the target and beacon is simultaneously optimized by the GO algorithm.

### IV. TLBC SECTION

As the front end of the proposed SCAL framework, the TLBC section proposes a processing mechanism on the simultaneous execution of target positioning and beacon calibrating. In it, the target is located through the observation of GP beacon, and the UP beacon is calibrated by target trajectory as in Fig.4. The whole TLBC section can be illustrated with 3 subsections.

#### A. LOCATING TARGET

This subsection of TLBC corresponds to the blue boxes of the flowchart in Fig.4, where the target observes 3 or more GP beacons, and its trajectory is located through ranging observation of GP beacons, as in Fig.5.

To ensure the real-time performance of the system and utilize the relevance of target trajectory points, the filtering method is selected to locate the target. When the number of observable GP beacons is 3 or more, the basic form of filtering used for target positioning is:

\[
\begin{align*}
X_k &= FX_{k-1} + W_k \\
Z_k &= h(X_k) + V_k
\end{align*}
\]  

(3)
where $X_k = [x_k, v_k, z_k] \in \mathbb{R}^{3} \times 1$ is estimated state of the target at time $k$, including position $X^p = [x_k, y_k, z_k]$ and speed $X^v = [v_{x,k}, v_{y,k}, v_{z,k}]$; $F = \begin{bmatrix} I_3 & T_3 & I_3 \\ 0_3 & I_3 \end{bmatrix}$ is prediction array, with $I_3$ for $3 \times 3$ Identity matrix and $T_k$ for time interval; $Z_k \in \mathbb{R}^{N_{\text{obs},k} \times 3}$ is the distance observation at time $k$, where $N_{\text{obs},k}$ is the number of observed GP beacons at time $k$; $W_k \in \mathbb{R}^{6 \times 1}$ and $V_k \in \mathbb{R}^{N_{\text{obs},k} \times 1}$ are respectively process noise and measurement noise, and two of them are mutually independent Gaussian processes; $h(\circ)$ is the observation update equation:

$$h(X_k) = \begin{bmatrix} \|X^p_{GP1} - X^k\|^2_2 \\
\|X^p_{GP2} - X^k\|^2_2 \\
\cdots \\
\|X^p_{GP_{N_{\text{obs},k}}} - X^k\|^2_2 \end{bmatrix}$$

(4)

where $X^p_{GP_i} = [x_{GP_i}, y_{GP_i}, z_{GP_i}]^T$ is the position of the $i_{th}$ observed GP beacon. Considering the high nonlinearity of (4) and the requirement for real-time performing, Cubature Kalman Filter (CKF) is adopted to locate the target [16], and $\hat{X}_k$ represents estimated state of target by CKF at time $k$.

**B. CALIBRATING UP BEACON**

This subsection of TLBC corresponds to the orange boxes of the flowchart in Fig.4, where the position of UP beacon is calibrated by target trajectory and the ranging observation relative to UP beacon, as in Fig.6.

In the blue area of Fig.6, the target can observe at least 3 GP beacons and the beacon $UP_i$. In this range, the beacon $UP_i$ can be calibrated according to the estimated target trajectory and the observation of $UP_i$, as in Fig.7:

$$k = k+1$$

**FIGURE 5.** The diagram of the target’s movement with the observation of GP beacon (the red solid hexagon for the GP beacon, the hollow hexagon for the UP beacon, and the blue area for execution area of this subsection of TLBC).

**FIGURE 6.** Diagram of the target’s movement for the calibration of UP beacon (the red solid hexagon for the GP beacon, the hollow hexagon for the UP beacon, and the blue area for execution area of this subsection of TLBC).

In Fig.7, based on estimated target trajectory set $\{\hat{X}_k\}$ in time $1 \rightarrow k$, a sub-set of target trajectory points relative to $i_{th}$ observed UP beacon $\{\hat{X}_{s,UP_i}\}$, $s = 1, 2, \cdots, S_i$, is selected, where $\hat{X}_{s,UP_i}$ is the estimated target trajectory point with $UP_i$ beacon and at least 3 GP beacons observed. According to $\{\hat{X}_{s,UP_i}\}$ and corresponding observations on $UP_i$ beacon $\{Z_{s,UP_i}\}$, the calculation of $P_{UP_i}$, the position of $UP_i$ beacon is modeled by the square error model:

$$E_{\text{LSE}}(P_{UP_i}) = \sum_{s=1}^{S} (||\hat{X}_{s,UP_i} - P_{UP_i}||_2^2 - Z_{s,UP_i})$$

(5)

An optimization based on Least Squares Error is:

$$\hat{P}_{UP_i} = \arg \min_{P_{GP_i} \in \mathbb{R}^3} [E_{\text{LSE}}(P_{UP_i})]$$

(6)

To ensure real-time performance, the Gauss-Newton optimization algorithm [17] is utilized to solve (6) Meanwhile as in Fig.4, $P_{UP_i}$ is stored for subsequent conversion into the location of GP beacon.

**C. GP BEACON GROUP EXPANSION**

This subsection of TLBC corresponds to the green boxes of the flowchart in Fig.4: the calibrated UP beacon is converted into a GP beacon, as in Fig.8.

To calculate the location of $UP_i$ beacon with enough observation, the converting mechanism follows: only if the number of GP beacons observed by the target is less than 3, $UP_i$ beacon with the currently most observation is converted into a GP beacon (as in the lower right corner of Fig.8), as $UP_i \rightarrow GP$, and the stored $P_{UP}$ transforms accordingly, as $P_{UP} \rightarrow P_{GP}$.
the basic observation equation is
During positioning the target trajectory in the TLBC section,
sub-sets of target trajectory.
evaluate the calibrating quality of beacons given different
target trajectory and correct the traditional GDOP through
target (anchors) in the TLBC section.
positioning accuracy can be reflected by GDOP.
the influence of different anchor distributions on the target
Geometric Dilution of Precision (GDOP). In other words,
cific distribution of reference anchors can be illustrated by
According to [18], the magnification relationship from the
position of target and beacon calibration in realtime.
based on the EGDOP is further proposed to globally optimize
the TLBC section. On this basis, a global optimization algorithm
between the target trajectory point and UP beacon at the
strate the mechanism of positioning error propagation
It is unrealistic and unnecessary to optimize all of these data
for realtime performing.
To solve it, a Geometric Dilution of Precision based on
Error Propagation (EGDOP) model is proposed to demonstrate
the mechanism of positioning error propagation between the target trajectory point and UP beacon at the
TLBC section. On this basis, a global optimization algorithm
based on the EGDOP is further proposed to globally optimize
the position of target and beacon calibration in realtime.

A. EGDOP MODEL
According to [18], the magnification relationship from the
ranging error to the target positioning error under the specific
distribution of reference anchors can be illustrated by
Geometric Dilution of Precision (GDOP). In other words,
the influence of different anchor distributions on the target
positioning accuracy can be reflected by GDOP.
However, when it comes to the localization of UP beacons,
the traditional GDOP obtained by the estimated trajectory
points is biased, due to the estimated position error of the
target (anchors) in the TLBC section.
To solve this problem, the Error Propagation (EP)
model [19] is utilized to derive the position error of the
target trajectory and correct the traditional GDOP through
error information. Hence, a Geometric Dilution of Precision
based on Error-propagation (EGDOP) model is proposed to
evaluate the calibrating quality of beacons given different
sub-sets of target trajectory.

1) POSITION ERROR OF ESTIMATED TARGET TRAJECTORY
During positioning the target trajectory in the TLBC section,
the basic observation equation is:
\[ d_{k,GP^{obs}} = \sqrt{(x_k-x_{GP^{obs}})^2+(y_k-y_{GP^{obs}})^2+(z_k-z_{GP^{obs}})^2} \] (7)
where \( GP^{obs} \) is the observed GP beacon; \( d_{k,GP^{obs}} \) is the
ranging observation between the target and the \( GP^{obs} \) beacon at time \( k \); \( [x_k, y_k, z_k] \) is the target position;
\( [x_{GP^{obs}}, y_{GP^{obs}}, z_{GP^{obs}}] \) is the \( GP^{obs} \) beacon position. According
to to (7), the error equation can be obtained by the total
differential form of (7) and the EP law [19]:
\[
\begin{bmatrix}
  m_{x_k,GP^{obs}}^2 \\
  m_{y_k,GP^{obs}}^2 \\
  m_{z_k,GP^{obs}}^2 \\
\end{bmatrix}
\begin{bmatrix}
  \alpha_{GP^{obs},k}^2 \\
  \beta_{GP^{obs},k}^2 \\
  \gamma_{GP^{obs},k}^2 \\
\end{bmatrix}
+ \begin{bmatrix}
  m_{x_{GP^{obs}}}^2 \\
  m_{y_{GP^{obs}}}^2 \\
  m_{z_{GP^{obs}}}^2 \\
\end{bmatrix}
\begin{bmatrix}
  \alpha_{GP^{obs},k}^2 \\
  \beta_{GP^{obs},k}^2 \\
  \gamma_{GP^{obs},k}^2 \\
\end{bmatrix}^T
= m_{x_{GP^{obs}}}^2 + m_{y_{GP^{obs}}}^2 + m_{z_{GP^{obs}}}^2
\] (8)
where \( [x_{GP^{obs}}, y_{GP^{obs}}, z_{GP^{obs}}] \) is the position error of the
\( GP^{obs} \) beacon; \( m_{x_{GP^{obs}}, y_{GP^{obs}}, z_{GP^{obs}}} \) is the ranging error at time \( k \);
\( [m_{x_k}, m_{y_k}, m_{z_k}] \) is the position error of target at time \( k \);
\( \alpha_{GP^{obs},k} = \frac{x_k-x_{GP^{obs}}}{d_{k,GP^{obs}}} \), \( \beta_{GP^{obs},k} = \frac{y_k-y_{GP^{obs}}}{d_{k,GP^{obs}}} \), \( \gamma_{GP^{obs},k} = \frac{z_k-z_{GP^{obs}}}{d_{k,GP^{obs}}} \) is the direction cosine of the target relative to \( GP^{obs} \) beacon.

The position error noise of \( GP^{obs} \) beacon (the error of GP beacons converted from UP beacons is derived from the
subsequent discussion) and the ranging error noise can be
acquired in advance. Hence for 3 or more \( GP^{obs} \) beacons,
an error equation system based on (8) can be obtained:
\[
A_E \begin{bmatrix}
  m_{x_k}^2 \\
  m_{y_k}^2 \\
  m_{z_k}^2 \\
\end{bmatrix} = B_E
\] (9)
where for the \( \text{N}_{th} \) \( GP^{obs} \) beacon, that is the \( GP^{obs}_{\text{N}} \) beacon,
\( (\text{N} = 1, 2, \cdots, \text{N}_{\text{obs}}, k) \):
\[
A_E = \begin{bmatrix}
  \alpha_{1,GP^{obs},k}^2 & \beta_{1,GP^{obs},k}^2 & \gamma_{1,GP^{obs},k}^2 \\
  \alpha_{2,GP^{obs},k}^2 & \beta_{2,GP^{obs},k}^2 & \gamma_{2,GP^{obs},k}^2 \\
  \vdots & \vdots & \vdots \\
  \alpha_{\text{N}_{\text{obs}},GP^{obs},k}^2 & \beta_{\text{N}_{\text{obs}},GP^{obs},k}^2 & \gamma_{\text{N}_{\text{obs}},GP^{obs},k}^2 \\
\end{bmatrix}
\] (10)
\[
B_E = \begin{bmatrix}
  m_{x_{1,GP^{obs}}}^2 \\
  m_{x_{2,GP^{obs}}}^2 \\
  \vdots \\
  m_{x_{\text{N}_{\text{obs}},GP^{obs}}}^2 \\
\end{bmatrix} + A_E \begin{bmatrix}
  m_{x_{1,GP^{obs}}}^2 \\
  m_{x_{2,GP^{obs}}}^2 \\
  \vdots \\
  m_{x_{\text{N}_{\text{obs}},GP^{obs}}}^2 \\
\end{bmatrix}
\] (11)

By performing the Least Squares Solution on (9), the positioning
errors on X, Y, and Z-axis of the target \([m_{x_k}, m_{y_k}, m_{z_k}]\)
can be obtained:
\[
\begin{bmatrix}
  m_{x_k}^2 \\
  m_{y_k}^2 \\
  m_{z_k}^2 \\
\end{bmatrix} = \left(A_E^T A_E\right)^{-1} A_E^T B_E
\] (12)
Therefore, the overall position error of the target is:
\[
m_{x_k} = \sqrt{m_{x_k}^2 + m_{y_k}^2 + m_{z_k}^2}
\] (13)
For \( \{ \hat{X}_{s,UP_i} \} \in \{ \hat{X}_k \} \), the same also exists:
\[
m_{Xs,UP_j} = \sqrt{m_{x1,UP_j}^2 + m_{y1,UP_j}^2 + m_{z1,UP_j}^2}
\]
(14)

2) EGDOP MODEL

Due to the position error of the trajectory set of \( \{ \hat{X}_{s,UP_i} \} \), the traditional GDOP of the estimated trajectory points relative to UP beacon has a deviation. To solve this problem, EGDOP with correction of the trajectory error \( m_{Xs,UP_i} \) is proposed.

According to \( m_{Xs,UP_j} \), the GDOP array of target trajectory relative to \( UP_i \) beacon weighted by error information:
\[
A_{EGDOP} = (A^T W_{UP_i} A)^{-1}
\]
(15)

where \( A \) is the direction cosine matrix of target trajectory relative to \( UP_i \) beacon [18], and \( W_{UP_i} \) is the weighting matrix based on \( m_{Xs,UP_j} \):
\[
W_{UP_i} = \frac{1}{\sum_{s=1}^5 m_{Xs,UP_j}^2}
\]
(16)

And the value of EGDOP by \( A_{EGDOP} \) is:
\[
EGDOP = \sqrt{\text{tr}(A_{EGDOP})}
\]
(17)

Among all of GP Beacons, the position error of the initial GP beacon can be acquired in advance. And the position of the rest GP Beacons converted from UP Beacons is obtained by the trajectory point \( \{ \hat{X}_{s,UP_i} \} \). According to [18], the positioning error of those GP Beacons can be calculated by \( A_{EGDOP} \) of the corresponding UP Beacons and the trajectory positioning error:
\[
\begin{align*}
    m_{xGP_j} &= (A_{EGDOP})_{1} \times \bar{m}_{s,UP_j}^2 \\
    m_{yGP_j} &= (A_{EGDOP})_{2} \times \bar{m}_{s,UP_j}^2 \\
    m_{zGP_j} &= (A_{EGDOP})_{3} \times \bar{m}_{s,UP_j}^2
\end{align*}
\]
(18)

where \( \bar{m}_{s,UP_j}^2 \) is the average position error of target trajectory on the X-axis, Y-axis, and Z-axis; \( (A_{EGDOP})_i \) represents the \( i \)-th diagonal element of the matrix \( A_{EGDOP} \).

B. TRAJECTORY SCREENING METHOD BASED ON EGDOP

In GO Section, to ensure the real-time performance of the system, it is necessary to select a specific set of points from all estimated target trajectory points for global optimization. Therefore, a screening mechanism for trajectory points based on EGDOP is proposed.

At time \( k \), for \( i \)-th UP beacon and its corresponding trajectory point set \( \{ \hat{X}_{s,UP_i} \} \), EGDOP can reflect the influence of different trajectory points on the positioning accuracy of the beacon. To be specific, the smaller the EGDOP is, the smaller the beacon positioning error caused by target positioning error is. EGDOP of \( \{ \hat{X}_{s,UP_i} \} \) relative to \( UP_i \) beacon is as in Fig.9

As in Fig.9, with the number of trajectory points increasing over time, the EGDOP gets smaller, and correspondingly, the beacon position calibration error gets smaller and according to (18), the positioning error of the beacon gets smaller.

However, when epoch = 781 (as in Fig.9), the EGDOP of several trajectory points drops relatively slowly. It is because trajectory points temporally at adjacent times are also spatially adjacent. When the value of EGDOP relatively is small the improvement of EGDOP is relatively limited under spatially adjacent conditions [18]. Correspondingly, it causes relatively limited improvement in the positioning accuracy of UP beacon, but a sharp increase in the computational complexity of global optimization.

To solve it, the number of trajectory points is effectively reduced by the screening method based on EGDOP. Considering the real-time requirement for the overall algorithm framework, the method of differential EGDOP is adopted to filter out trajectory points \( \{ \hat{X}_{s,UP_i} \} \). And in the new set \( \{ \bar{X}_{1,UP_i} \} \), the difference \( \Delta W_{EGDOP} \) between EGDOPs of any two adjacent points meet:
\[
|\Delta W_{EGDOP}| > \eta
\]
(19)
\[
\eta = \eta_0 \vartheta^n
\]
(20)

where \( n \) represents the epoch; \( \eta \) is the screening threshold; \( \eta_0 \) is the initial value of the screening threshold; \( \vartheta \) is the attenuation factor, whose value ranges from to 1.

At the beginning of the trajectory where EGDOP drops faster, according to (20), the \( \eta \) is relatively larger, which helps to select as few trajectory points as possible, to speed up the screening process. In the subsequent part where the decline of EGDOP is slowed down, according to (20), \( \eta \) is effectively reduced. In this case, it ensures that the overall EGDOP is small enough to accurately locate the position of...
the UP beacon at a stable screening rate. For \( UP_i \) beacon, the screening process for trajectory points based on EGDOP is specifically displayed in Fig.10.

![FIGURE 10](image)

The simulation is performed according to Fig.10 (the used trajectory point set \( \hat{X}_{s,UP} \) comes from the simulation in Section VI). As in Fig.11, compared to the 781st epoch of \( \hat{X}_{s,UP} \), the screened point set \( \hat{X}_{l,UP} \) can reach 1 at the 72nd epoch. The detailed results are shown in Table.1.

![FIGURE 11](image)

| Table 1. EGDOP of different trajectory point sets. |
|-----------------------------------------------|
| Epoch of unfiltered set | 2.00 | 1.50 | 1.20 | 1.00 | 0.308 | 0.289 |
|--------------------------|------|------|------|------|-------|-------|
| 403 | 601 | 715 | 781 | 1106 | 1203 (end) |
| Epoch of filtered set    | 42   | 53   | 61   | 72   | 103 (end) |

For the Gauss-Newton optimization algorithm [20], the relationship between computational complexity and the number of tracepoints \( N_{trace} \) is:

\[
\text{computational complexity} \propto O ((N_{trace})^3) \quad (21)
\]

As in Table.1, compared with the unfiltered \( \{ \hat{X}_{s,UP} \} \), the positioning performance of \( \{ \hat{X}_{l,UP} \} \) screened by differential EGDOP is slightly reduced (EGDOP increases from 0.289 to 0.308), but the \( N_{trace} \) of \( \{ \hat{X}_{l,UP} \} \) is significantly reduced. In other words, according to (21), the computational complexity of Gauss-Newton optimization has been greatly reduced.

C. GLOBAL OPTIMIZATION ALGORITHM BASED ON EGDOP

By screening method based on EGDOP, the point set \( \{ \hat{X}_{l,UP} \} \) related to the \( UP_i \) beacon is selected in original time \( 1-k \), and then the overall point set \( \{ X_\zeta \}, \zeta = 1, 2, \cdots, L \) including all \( \{ \hat{X}_{l,UP} \} \) is obtained.

At time \( k \), construct \( \xi = [X_0, X_1, \cdots, X_L, P_{UP_1}, \cdots, P_{UP_P}] \) as the optimized variable, and the weighted least square error model based on error information is:

\[
E_{Global}(\xi) = E_{Global}( [X_0, X_1, \cdots, X_L, P_{UP_1}, \cdots, P_{UP_P}] )
\]

\[
= \sum_{n=1}^{L} \sum_{l=1}^{T} W_{GP_l}( ||\hat{X}_n - P_{GP_l} ||_2 - Z_{n,GP_l} )^2
+ \sum_{n=1}^{L} \sum_{l=1}^{T} W_{UP_l}( ||\hat{X}_n - P_{UP_l} ||_2 - Z_{n,UP_l} )^2
\]

(22)

where, \( W_{GP_l} \) and \( W_{UP_l} \) are weighting factors based on observation error:

\[
W_{GP_l} = 1 - \frac{m^2_{d_k,GP_l}}{\sum_{n=1}^{T} m^2_{d_k,GP_n} + \sum_{n=1}^{L} m^2_{d_k,UP_n}}
\]

(23)

\[
W_{UP_l} = 1 - \frac{m^2_{d_k,UP_l}}{\sum_{n=1}^{T} m^2_{d_k,GP_n} + \sum_{n=1}^{L} m^2_{d_k,UP_n}}
\]

Then, an optimization model based on Least Square Error:

\[
\hat{\xi} = \arg \min_{\xi \in \mathbb{R}^{(L+1)} \times \{ \} } [ E_{Global}(\xi) ]
\]

(24)

The above optimization is solved by the Gauss-Newton optimization algorithm [17].
VI. SIMULATION

Through the UWB ranging simulation in which the target performs three-dimensional motion and planar motion, the positioning performance of the GO section of the proposed SCAL algorithm framework is evaluated. And the distribution of 6 GP beacons and 8 UP beacons is as in Fig. 12:

In Fig. 12, the distance between beacons on the Y-axis is 4.44m (40/9 m) within a range of 40m; the distributing gaps between adjacent beacons on X-axis and Z-axis are 3.2m and 2.1m, respectively. The configuration parameters of UWB are: the max range of signal covering (semi-diameter) is 12m, and the ranging error noise is a Gaussian process, with a standard deviation of 0.1m.

A. SIMULATION OF THREE-DIMENSIONAL MOTION

The target performs the random three-dimensional movement, and its movement diagram is as in Fig.13:

The simulations of three-dimensional motion are repeated 10 times (Fig.13 is one). They compare the SCAL algorithm based on the TLBC+GO section with the SCAL algorithm based only on the TLBC section as in Fig.14 and Table.2.3.

TABLE 2. The Root Mean Squared Error (RMSE) of target.

| RMSE | Only TLBC (m) | GO+TLBC (m) |
|------|---------------|-------------|
| X-axis | 0.2064 | 0.1789 |
| Y-axis | 0.0787 | 0.0689 |
| Z-axis | 0.2702 | 0.2228 |
| All axes | 0.3491 | 0.2940 |

According to Fig.14 and Table.2: compared with the SCAL algorithm without the GO section, the SCAL algorithm with GO+TLBC section has improved the positioning accuracy of the target on the X-axis by 13.32% (from 0.2064m to 0.1789m); the positioning accuracy on Y-axis has been improved 12.45% (0.0787m to 0.0689m); the positioning accuracy on Z-axis has increased by 17.54% (0.2702m to 0.2228m); the overall positioning accuracy has been improved by 15.78% (0.3491m to 0.2940m).

According to Fig.14 and Table.3: compared with the SCAL algorithm without the GO section, the SCAL algorithm with GO+TLBC section has improved the calibrating accuracy of UP beacons on average by 72.35% (0.5279m to 0.1459m).

After adding the GO section, the system’s positioning accuracy of the target and the beacons has been significantly improved, and the improvement of the beacon calibrating accuracy is particularly significant. Therefore, the result demonstrates the positioning improvement of the proposed GO algorithm based on EGDOP on the SCAL framework under three-dimensional target motion.

B. SIMULATION OF PLANAR MOTION

The target performs the random planar movement, and its movement diagram is:

The simulations of planar motion are repeated 10 times (Fig.13 is one). They compare the SCAL algorithm based on the TLBC+GO section with the SCAL algorithm based only on the TLBC section, as in Fig.16 and Table.4-5.

TABLE 4. The RMSE of target.

| RMSE direction | Only TLBC (m) | GO+TLBC (m) |
|----------------|--------------|-------------|
| X-axis         | 0.2148       | 0.2048      |
| Y-axis         | 0.0688       | 0.0652      |
| Z-axis         | 0.2955       | 0.2847      |
| All axes       | 0.3717       | 0.3567      |

According to Fig.16 and Table.4: compared with the SCAL algorithm without the GO section, the SCAL algorithm with GO+TLBC section has improved the positioning accuracy of the target on the X-axis by 4.66% (0.2148m to 0.2048m); the positioning accuracy on Y-axis has been improved 5.23% (0.0688m to 0.0652m); its positioning accuracy on Z-axis has increased by 3.65% (0.2955m to 0.2847m); the overall...
According to Fig. 14 and Table 3: compared with the SCAL algorithm without the GO section, the SCAL algorithm with GO + TLBC section has improved the calibrating accuracy of UP beacons on average by 57.31% (0.6990 m to 0.2983 m).

After adding the proposed GO section, the target positioning accuracy is slightly improved by 4.04%, and the overall accuracy reached 0.3567 m. Besides, on Z-axis, the maximum positioning error of the target is reduced from 1.19 m to 0.55 m. Also, the average calibration accuracy of UP beacons is significantly improved by 57.31% and reaches 0.2983 m.
Therefore, the result demonstrates the positioning improvement of the proposed GO algorithm based on EGDOP on the SCAL framework under the planar motion.

VII. EXPERIMENT
To further evaluate the performance of the proposed SCAL algorithm, by utilizing the supermarket passageway as an actual indoor scenario, a positioning experiment is constructed. The two-dimensional diagram of the beacon system is as in Fig.17:

The reference location of beacons is accurately calibrated by laser rangefinder (accuracy reaches 1 cm level). The experimental environment and equipment areas in Fig.18-20:

The LinkTrack P in Anchor Mode is selected as the UWB beacon, and the LinkTrack P in Receiver Mode bound to the cart in Fig.20 is selected as a UWB receiver with a sampling frequency of 25 Hz and a fixed height of 0.93 m (as a reference position on Z-axis). Bound to the car, a SLAMTEC M1M module (LIDARSLAM [21]) provides a trajectory with an accuracy of 0.02 m, which is treated as the reference position on the X-axis and Y-axis.

After GO processing, positioning results output at the frequency of 5 Hz, and the movement trajectory of the car is shown in Fig.21. The experiment compares the proposed SCAL algorithm framework based on EGDOP-GO with the SCAL algorithm based on the Backward Processing with Inverse Trajectory [15], as in Fig.21 and Table.6-7.

According to Table.6-7, compared with the SCAL algorithm based on Backward Processing, the proposed SCAL algorithm based on EGDOP-GO improves the positioning accuracy of the target trajectory on the X-axis by 24.41% (0.1901 m to 0.1437 m); the positioning accuracy...
on the Y-axis increases by 55.18% (0.0908m to 0.0407m); the positioning accuracy on Z-axis increases by 42.82% (0.3629m to 0.2075m); overall positioning accuracy has been improved by 39.06% (0.4196m to 0.2557m); the average calibration accuracy for 8 beacons has increased by 47.97% (0.4684 to 0.2437). Besides, according to Fig.22, compared with the backward process, the proposed SCAL algorithm has more efficient parallel computation on the GO section and
FIGURE 23. The positioning error of the target and the calibrating error of UP beacons.

TLBC section and can reach real-time standard with the outputting frequency of 5Hz.

According to Fig.23, the SCAL algorithm based on Backward Processing has limited positioning performance, especially within the middle part of the beacon system, but the proposed SCAL algorithm illustrates more accurate and comprehensive positioning performance on the whole beacon system: the positioning accuracy of the target is improved by 39.06% and reaches 0.2557m, with maximum positioning error on Z-axis reduced from 1.46m to 0.57m; and the calibration accuracy of UP beacons has been improved by 47.97% and reaches 0.2437m.

VIII. CONCLUSION

Under simultaneous beacon-calibrating and target-positioning, the real-time positioning and calibrating accuracy in indoor scenarios are significantly reduced. To solve it, a novel SCAL algorithm framework is proposed, which is divided into the TLBC section and GO section. In a typical distributed beacon layout, by a processing mechanism of synchronous acquisition of target position and beacon position, the initial positioning of target and beacon is achieved in the TLBC section. In the GO section (parallel to TLBC section), a global optimization algorithm based on EGDOP is proposed, which utilizes the EGDOP model to filter out the set of trajectory points for optimization, and then performs global optimization on the positioning of target trajectory and beacons in realtime. By simulation, we verify that the GO algorithm based on EGDOP significantly improves the positioning performance under the target’s planar motion and three-dimensional motion. By experiments, we verify that compared with the SCAL algorithm based on Backward Processing with Inverse Trajectory, the proposed SCAL algorithm illustrates more comprehensive and more efficient
positioning performance and its positioning accuracy of target trajectory and beacons are improved respectively by 39.06% and 47.97%, and reach 0.2557m and 0.2437m, respectively.

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