Unmanned Visual Localization Based on Satellite and Image Fusion

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ABSTRACT Unmanned driving is an important means for future human to achieve locomotion, and it will have broad application prospects. The unmanned vehicle still has the following difficulties in its long distance displacement: Single source sensor cannot meet the requirements of the positioning accuracy of the changeable and complex scenes, and the image analysis accuracy of visual processing in complex interference needs to be improved. In order to solve these problems, an unmanned vision localization algorithm based on multi-sensor fusion is proposed in this paper, by analyzing the positioning perception accuracy of unmanned vehicle, the precision and range of different perception methods at large, medium and small scales are obtained. A vision localization algorithm of multi-source fusion based on pseudo-range equivalence is designed in this paper. In order to reduce the influence of image distortion on localization accuracy, a visual localization algorithm based on image feature matching is proposed. The localization accuracy in complex environment is effectively improved by the multi-source fusion localization algorithm of pseudo-range equivalence. The MATLAB simulation shows that the positioning accuracy of the unmanned driving is improved to a certain extent at different scales.

1. INTRODUCTION
Unmanned vehicle is an automatic displacement technology which uses human-like logic to endow intelligence to machinery. It effectively maps the virtual computing space with the real vehicle and route, and lays a space-time foundation for the diffusion of computational intelligence from small scale to urban scale.

In order to realize group, automatic and precise unmanned driving, we need the cooperation of perception, communication, computing, storage, control, decision-making and feedback, and effectively promote the development of sensor, 5G mobile communication, Internet of Things, large data, cloud computing and other related technologies.

Unmanned driving is an important means to realize human position moving in the future, which has attracted great attention of the world powers. In September 2017, the U.S. federal government formally passed the world's first Driverless Vehicle Act to promote the development of driverless systems and services at the national level. In 2014, the U.S. Department of Transportation and ITS Joint Projects Office jointly proposed ITS Strategic Plan 2015-2019(ITS Strategic Research Plan, 2015-2019), which...
upgraded unmanned technology planning to a dual development strategy of networking and automated control intelligence, and with a focus on breakthroughs in enhancing traffic mobility and supporting information sharing of traffic system and so on. In May 2018, the European Union announced a schedule to strive to enter a fully automatic driving society by 2030, focusing on improving vehicle computing capabilities, and through the accelerated popularization of electric vehicles, in-depth research and development of automatic driving, the integration of automotive computers into digital transport networks to promote the rapid landing of driverless technology. In June 2018, the Japanese government proposed to achieve driverless driving in Tokyo in the 2020 Olympic Games. Regarding China, in May 2015, the "Made in China 2025" put forward by the State Council which explicitly calls for the development of smart vehicles and promoting intelligent vehicles.

According to the latest report from Intel and Strategy Analytics, the technology analysis consulting firm, the global industry related to driverless cars will reach $7 trillion by 2030 and the Chinese market for driverless vehicles will reach $2.5 trillion by 2030.

With the gradual development of driverless technology, there are still some important problems that need to be solved urgently:

1) Single source sensors cannot meet the positioning accuracy requirements of several variable and complex scenes. The displacement process of the carrier is essentially a process of adaptation to the environment. Large-scale displacement needs to undergo a combination of direction, slope, width, and so on. And the number of combinations increases exponentially with the increase of particle size. However, the traditional single-source sensor cannot complete the perception and matching of complex and changeable environment because of its own power and sensing scale limitations.

2) The accuracy of image processing under complex interference should be improved. Vision is the perceptual organ of human intelligence. It needs the effective cooperation of camera, sensor network and computing system to transfer it to AI. Various kinds of interference in various information transmission channels, especially illumination changes, sensor jitter, background clutter, occlusion and scale changes, will cause image distortion in the "brain".

To solve the above problems, this paper carries out unmanned visual localization algorithm of multi-source sensor fusion, through the analysis of positioning perception accuracy in unmanned driving to obtain the precision and range of different perception means in large, medium and small scales. A multi-source fusion vision localization algorithm based on pseudo-range equivalence is designed. In order to reduce the influence of image distortion on localization accuracy, a visual localization algorithm based on image feature matching is proposed. And the localization accuracy in complex environment is effectively improved by multi-source fusion localization algorithm of pseudo-range equivalence. The MATLAB simulation shows that the positioning accuracy of the unmanned driving is improved to a certain extent at different scales.

2. THE BASIC THEORY OF HETEROGENEOUS SENSOR LOCATION

2.1 Basic principle of large scale satellite positioning: distance determination

Satellite positioning is an important method to determine the coordinates of the uncovered targets on the earth's surface by using the geosynchronous orbit reference point and the geometric positioning principle. The basic principles are as follows: The time information of the signal arriving at the receiver is obtained by detecting the signal transmitted by satellite through the ground satellite navigation receiver, and the distance between the satellite and the receiver is obtained by transforming the relationship of time and distance. Finally, the coordinate points of the target are obtained by combining several satellites and performing geometric calculation. The conversion from signal measurement phase to arrival time information is an important means of satellite positioning, as shown in Figure 1. If there is a pseudo range of $p$:

$$p = c \Delta t = c \tau + c (\Delta b_u - \Delta b_i) + \Delta D + \Delta \rho_{trop} + \Delta \rho_b \tag{1}$$

In the formula, $\tau$ is theoretical arrival time difference, $b_u$ and $b_i$ is satellite clock error at different time points, $c$ is transmission speed of electromagnetic wave, $\Delta D$ is ephemeris equivalent distance error,
Δρ_{trop} is ionospheric refraction correction, Δρ_n is receiver noise error. And the following formula can be obtained by joint observation of multiple satellite sources.

\[ c \times \tau_i = \sqrt{(X_i - X_u)^2 + (Y_i - Y_u)^2 + (Z_i - Z_u)^2} + C(2) \]

In formula (2), \( \tau_i \) is observed quantity from different satellite sources, \( X, Y, Z \) is target coordinates of calculation, \( C \) is error source, \( C = \Delta D + \Delta \rho_{trop} + \Delta \rho_n \). It can be seen that the errors of satellite positioning mainly come from ephemeris error, ionospheric error and geometric error, as shown in Figure 1.

\[ \Delta \rho_{trop} = \Delta \rho_1 + \Delta \rho_2 + \Delta \rho_3 + \Delta \rho_4 \]

Because the variance of large-scale coverage varies little, ephemeris error and ionospheric error can be effectively reduced by ground difference. While the positioning targets are mainly concentrated on the ground, and the statistical proportion of the shaded area is more than that of the open area, which results in the destruction of the basic point distribution of geometric solution as well as the increase of positioning error. The accuracy of general satellite positioning is about 5~20 meters.

2.2 Basic principles of mesoscale wireless networks location: area determination

Wireless sensor network location method is based on a small number of nodes with known location, using its own transmission of the required radio wave signal characteristic parameters to calculate the location of unknown nodes. According to whether using distance measurement or not, it is divided into ranging algorithm and range-free algorithm. Ranging algorithm measures the relative distance or azimuth between nodes to get the actual distance, so that the position of unknown nodes can be calculated. Generally speaking, the positioning accuracy of ranging algorithm is higher than range-free algorithm, but the hardware requirements of the former are higher, and the ability to resist noise is relatively weak.

There are mainly 4 kinds of location methods based on ranging: RSS(Received Signal Strength), TOA(Time of Arrival), TDOA(Time Difference of Arrival) and AOA(Angle of Arrival), different algorithms are adapted to different location scene and accuracy requirements. This paper mainly discusses the positioning results using TDOA as location method. As the name implies, TDOA is a method that uses time difference to achieve positioning, that is, by measuring the time difference of signals arriving at each monitoring station to calculate the location of the signal source.

The node 1 is used as the measuring reference node, and the distance difference of remaining nodes is:

\[ \hat{r}_i = (d_i - d_1) + n_{di} = \sqrt{(x - x_i)^2 + (y - y_i)^2} - \sqrt{(x - x_1)^2 + (y - y_1)^2} + n_{di} \]

In the above formula, \( n_{di} \) represents measurement noise, and the measured time difference is:

\[ \tau_i = \frac{\hat{r}_i}{c}, i = 2, 3, \cdots, N \]

Among them, \( c \) represents the speed of signal propagation.

If the error in formula (3) is not considered, the TDOA equation can be expressed as:


\[ c \cdot \tau_1 = \sqrt{(x - x_1)^2 + (y - y_1)^2} - \sqrt{(x - x_2)^2 + (y - y_2)^2} \quad (5) \]

TDOA positioning accuracy mainly depends on the accuracy of time difference measurement. Generally speaking, when the time difference error is about 100 ns, the positioning accuracy of this method can reach about 30 m. However, only using a single ranging algorithm for calculation often cannot meet the requirement of precise positioning, such as TDOA localization method usually needs to be used in conjunction with other methods.

2.3 Basic principle of small scale inertial device location: direction determination

Small-scale inertial device positioning technology is widely used in aviation, aerospace and vehicle positioning and navigation fields due to its strong autonomy, anti-interference and good concealment. It mainly uses the target motion data collected by the inertial sensor terminal to achieve positioning. For example, acceleration sensors and gyroscopes located in the target can measure a series of information such as speed, acceleration, direction of the target. Then, based on the dead reckoning algorithm, the position information of the target is obtained by corresponding calculation, as shown in Figure 2.

Based on the premise of short-term navigation, the positioning accuracy of inertial device can reach 15 m at 30 s and will rise to 70-80 m at 60 s. That is because although the inertial navigation positioning based on dead reckoning algorithm has the advantages of data stabilization and no dependence, it also has the characteristics of cumulative error over time, which is the biggest limitation of inertial device localization.

3. VISUAL LOCALIZATION ALGORITHM OF MULTI-SOURCE FUSION BASED ON PSEUDO-RANGE EQUIVALENCE

3.1 Analysis of the problems of heterogeneous sensor location

From start to finish, unmanned driving is a complex process of condition and environment adaptation. In order to accurately analyze the combined errors of unmanned vehicles, it is necessary to subdivide the multiple processes of state change, as shown in Figure 3. Different process divisions are mainly based on the completeness of different number and types of locating sources in each process, thus inferring the problems in improving the locating accuracy.

(1) Satellite state incomplete process: Unmanned large-scale navigation path planning relies on wide coverage of satellite navigation, as in Figure 3, starting point A to starting point B. However, the satellite navigation signal is weak, and it is impossible to obtain enough positioning datum in the urban canyon and under the bridge, that is, the geometric distribution in formula (2) is destroyed. At this time, other positioning means are needed to help improve the accuracy of real-time localization.

(2) Fast baseline collaboration for real-time control: When the unmanned vehicle needs to change the line or avoid collision, the acceleration and direction of driving are determined by the inertial device, and the obstacles are determined by the visual system formed by video and intelligent control. And the inertial device has the problem of long-term accurate drift, but short-term locating accurately, and the positioning accuracy of the visual system is precisely determined by video acquisition. Therefore, in order to ensure the safety of driverless vehicles, rapid positioning means of real-time control is needed.
3.2 Visual location algorithm based on image feature matching

Unmanned vehicles need to respond in milliseconds to avoid obstacles during driving, so they are required to accurately identify the relative position of objects in the scene. The basic principle of visual positioning system is to compare the captured image with the pre-stored image, and the difference between them reflects the distance and angle between them. Here, a characteristic source image on the road is set to be \( P_0(x, y) \), and the measured images obtained from different distances and angles are \( Q_j(x, y) \), then the corresponding errors and measurements are collected and measured in advance.

\[
D(x, y) = \sum_{j=0}^{J-1} \sum_{k=0}^{K-1} |P_j(x + j, y + k) - Q_j(x, y)|^2
\]

In the formula, \( j \) and \( k \) correspond to distance and angle respectively, and the following formula can be obtained by further changes.

\[
DS(x, y) = \sum_{j=0}^{J-1} \sum_{k=0}^{K-1} |P_j(x + j, y + k)|^2
\]

It is the energy of the corresponding area of the template in the source image, which is related to the pixel position \( (x, y) \), but the \( DS(x, y) \) changes slowly with the pixel position \( (x, y) \). At this point, in order to further reduce the error, \( DS(x, y) \) is normalized cross-correlation, and gray morphological etching operation is carried out to remove the peak noise of the image, then expansion operation is done to remove the low-valley noise of the image.

\[
R(x, y) = \frac{\sum_{j=0}^{J-1} \sum_{k=0}^{K-1} Q_j(x, y) P_j(x + j, y + k)}{\sum_{j=0}^{J-1} \sum_{k=0}^{K-1} P_j(x + j, y + k) \sum_{j=0}^{J-1} \sum_{k=0}^{K-1} Q_j(x, y) P_j(x + j, y + k)}
\]

When \( x \) and \( y \) change, \( Q_j(x, y) \) transforms in the source image area and gets all values of \( R(x, y) \). The maximum of \( R(x, y) \) indicates the most precise location for matching \( Q_j(x, y) \). If a region of the same size as the measured image is extracted from the source image, the matching location information \( J \) and \( K \) can be obtained.

3.3 Multi-source fusion location algorithm based on pseudo-range equivalence

From the above, ranging, time, field strength, geomagnetism, and so on, are different characteristic quantities, which need to be converted into unified representation quantities when they are solved at the same time. In this paper, pseudo-range is used to solve multi-source fusion localization and it is set to be \( M_i \).

Assuming that the error does not change in time and space, the observation error can be written as

\[
\begin{align*}
M_1 &= \sqrt{(X^i - X_u)^2 + (Y^i - Y_u)^2 + (Z^i - Z_u)^2} + C_1 \\
M_2 &= \sqrt{(X^i - X_u)^2 + (Y^i - Y_u)^2 + (Z^i - Z_u)^2} + C_2 \\
M_3 &= \sqrt{(X^i - X_u)^2 + (Y^i - Y_u)^2 + (Z^i - Z_u)^2} + C_3
\end{align*}
\]
The Kalman filter is used to modify the information so as to get the final correction result of target position. It is assumed that it is the location, \( t = (t_x, t_y, t_z)^T \), of different positioning sources aiming at the unified target reference system, then there are

\[ M_i = M_k + t \tag{10} \]

And the different state values \( M_{ik} \) of different locating sources are obtained, then the fusion combination closest to \( t \) can be obtained by successive approximation, where the location error is minimum.

4. SIMULATION AND ANALYSIS

4.1 Building simulation environment

In order to prove the validity of the proposed algorithm—unmanned vision positioning of multi-sensor fusion, the performance of the algorithm will be verified by MATLAB. Then setting satellite navigation for large-scale positioning, inertial navigation and vision as a benchmark for small-scale positioning. In the experiment, the sampling period is 1s, the number of sampling points is 3000, and the initial value of the state vector is \([0 \ 10 \ 0 \ 0 \ 10 \ 0] \). Monte Carlo method is used as a reference for repeated tests, and collecting the errors of unmanned vehicle in localization and direction selection.

4.2 Positioning accuracy analysis of large scale unmanned vehicle

![Fig. 4 error of satellite positioning and inertial navigation positioning in unmanned driving](image)

From the graph, we can see that the result of satellite positioning is more stable than that of inertial navigation, of which the error range is basically within 50m. The initial positioning effect of INS is better, but as time goes on, the algorithm has the limitation of error superposition, which leads to rapid divergence of the later positioning results, and the positioning accuracy is getting worse and worse, which cannot guarantee the positioning requirements of high precision. Therefore, it is not advisable to use DR algorithm to target location alone.

4.3 Positioning accuracy analysis of small scale unmanned vehicles

Figure 5 shows the actual effect of using visual methods to distinguish road markings.
Fig. 5 image matching effect of small scale in unmanned driving—changing line

It shows the original image collected from the video, after RGB feature extraction, and then processed by different color clustering algorithm, and then the resulting image is denoised by morphological closed operation. From the experimental results, it can be seen that the image processed by the algorithm can effectively identify the road situation of original image, and can get a clearer denoising effect map, which can provide support for small-scale behavior of location matching and motion control.

5. CONCLUSION

In this paper, the unmanned vision localization algorithm based on multi-source sensor fusion is developed, and a vision localization algorithm of multi-source fusion based on pseudo-range equivalence is designed. In order to reduce the influence of image distortion for location accuracy, a visual localization algorithm based on image feature matching is proposed, and it is solved by multi-source fusion localization algorithm based on pseudo-range equivalence. Finally, it effectively improves the positioning accuracy under complex environment, and the method has important reference value for practical engineering application in related fields.

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