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Key technology of mine underground mobile positioning based on LiDAR and coded sequence pattern

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Abstract: Technologies of underground mobile positioning were proposed based on LiDAR data and coded sequence pattern landmarks for mine shafts and tunnels environment to meet the needs of fast and accurate positioning and navigation of equipments in the mine underground without satellite navigation signals. A coded sequence pattern was employed for automatic matching of 3D scans. The methods of SIFT feature, Otsu segmentation and fast hough transformation were described for the identification, positioning and interpretation of the coded sequence patterns, respectively. The POSIT model was presented for speeding up computation of the translation and rotation parameters of LiDAR point data, so as to achieve automatic 3D mapping of mine shafts and tunnels. The moving positioning experiment was applied to evaluating the accuracy of proposed pose estimation method from LiDAR scans and coded sequence pattern landmarks acquired in an indoor environment. The performance was evaluated using ground truth data of the indoor setting so as to measure derivations with six degrees of freedom.
Key words: LiDAR; coded sequence pattern; mobile positioning; SLAM algorithm; POSIT algorithm

1 Introduction

The development of global navigation satellite system (GNSS) has brought great convenience to the work and life of mankind. However, there are still a lot of problems to be resolved for fast and accurate positioning in mine shafts and tunnels environment without GNSS signals. Unmanned mining technique, also named as manless working face, is the only way to solve the safety problem of mine industry. While the core technology of underground unmanned mining is the high-speed, high-precision self-positioning, self-orientation, pose estimation and navigation of underground mining, digging, and transportation equipments.

Currently, the underground positioning technologies include [1]: radio frequency identification (RFID) [2], ZigBee technology [3], infrared technology [4], Bluetooth [5], WiFi and other wireless positioning technology. The pose parameters of moving targets can be estimated by the means of wireless signal receivers fixed on targets and the wireless base station installed in the tunnels. Nowadays, the moving targets can be located in the range of about 5 m. However, its accuracy is unable to meet the needs of unmanned mining and smart mining.

Active positioning technologies, including laser range finders, light detection and ranging (LiDAR), visible light image sensors, can be used for perceiving the surrounding environment. The active positioning technologies are characterized with ease of hardware integration and software operating without depending on wireless base station signal. The data from active positioning system can be used to correct accumulated errors of IMU module.

3D point cloud information can be scanned by the LiDAR sensors installed on a mobile platform. The features of LIDAR point cloud data include large volumes of data, irregular distribution of points, lack of texture information and so on. The LiDAR sensor can only get a certain part of the spatial information of the

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scene in each scan due to object occlusion, narrow underground tunnels and other restrictions during the mobile laser scanning.

All the 3D point cloud data from different perspectives in the tunnel should be transformed to a common coordinate system, also known as the global reference coordinate system, to achieve a continuous positioning of moving targets. Matching 3D scans is one of the most critical works in the process of the mobile positioning, and it will directly affect the final accuracy of positioning.

Currently, the problem of automatic registration of point cloud data has not yet been fully resolved. The common ICP registration algorithm needs two point data with the close initial position and orientation, and quite large overlap regions. The ICP iterative registration operation is time-consuming so as to fail to meet the needs of real-time positioning fast moving targets.

Simultaneous localization and map building (SLAM) is a technique used by robots and autonomous vehicles to build up a map within an unknown environment (without a prior knowledge) or to update a map within a known environment (with a priori knowledge from a given map), at the same time to keep track of their current location. For example, MonoSLAM [6] is a vision-based simultaneous localization and mapping system. MonoSLAM system integrates a single camera to detect and track a sparse number of landmark features, and also plots its position within a 3D map. It is an interesting way of doing things because it involves forming a closed loop between the mapping and the feature detection. Individual features are detected and inserted into the map, but then the map is used for very specifically searching and re-acquiring previously observed features.

6DSLAM [7] system registers 3D point clouds into a common coordinate system. For the registration, different iterative closest point (ICP) [8] minimizing algorithms can be chosen, as well as global relaxation methods, aiming at generating an overall globally consistent scene so as to locate the moving target in such 3D map.

The shafts and tunnels in underground mine are harsh with humid air and ambient light. Therefore MonoSLAM, which is totally based on imaging technology, is not suitable for such environment. In the case of 6DSLAM system, ICP algorithm is used for registering 3D scanning point clouds. Although k-dimensional tree data structure is employed for optimizing the data search, it still takes several seconds for achieving the overall registration of 3D point cloud so as to unable to meet the needs of real-time positioning.

According to the features of mine underground shafts and tunnels environment, a coded sequence pattern landmark is proposed for automatic matching of LiDAR point data. The methods including SIFT [9] features, Otsu segmentation and fast hough transformation is described for identification, positioning and interpret of the coded sequence patterns, respectively. The POSIT model is presented for computing the translation and rotation parameters of 3D scans to achieve matching of LiDAR point data and automatic 3D mapping of mine underground shafts and tunnels.

2 Algorithm overview

As shown in Fig. 1, the preparatory work includes establishment of the coded sequence pattern landmarks network along the underground tunnels. The 3D center coordinates of coded sequence pattern landmarks are acquired during the installation process to set up landmarks' database.

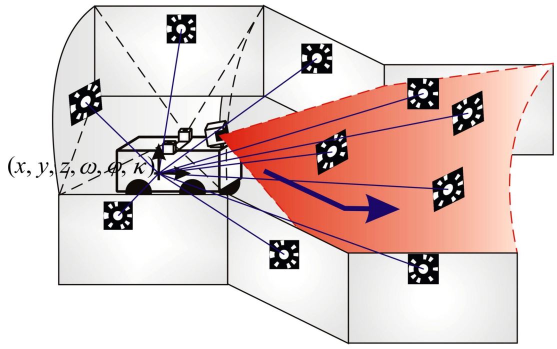

Fig. 1 Schematic of LiDAR and coded sequence pattern-based pose estimation

The flow chart of mobile localization algorithm is shown in Fig. 2. The steps of positioning algorithm are as follows.

1) Data acquisition: The camera captured images which contain coded sequence pattern landmarks and LiDAR obtained 3D point cloud information of the tunnel environment during the target moved along the tunnels.

2) Image processing: The coded sequence pattern landmarks were rapidly identified from camera images based on SIFT [10] features. Then the 3D center coordinates of the landmarks were acquired by decoding from database.

3) POSIT: The pose from orthography and scaling with iterations (POSIT) model [11] was employed for iterative calculation of the position and orientation parameters of the 3D scans if the number of noncoplanar coded pattern landmarks obtained by cameras is not less than four.

4) Registration: The registration of 3D point cloud can be achieved according to the pose parameters to

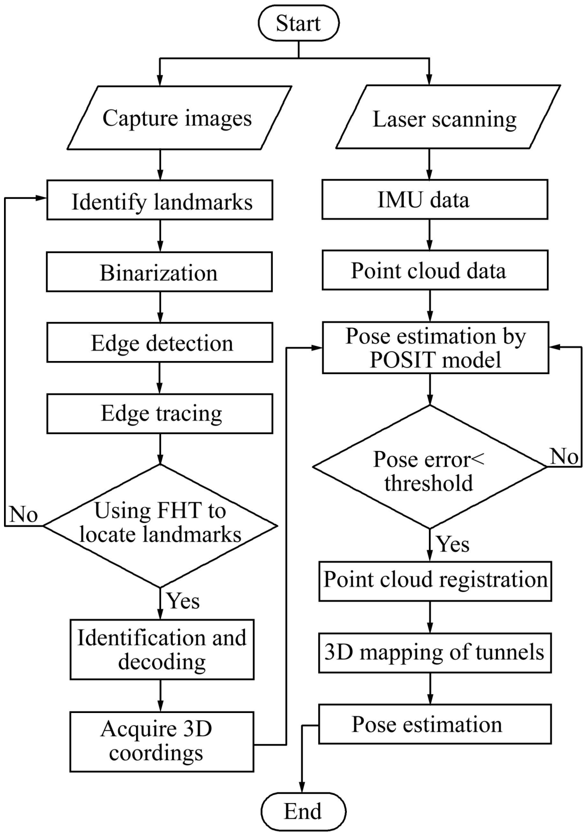

Fig. 2 Flow chart of LiDAR and coded sequence pattern-based pose estimation

calculate the position and orientation of moving targets and build the 3D map of mine tunnels.

3 Coded sequence pattern landmarks

Figure 3 demonstrates the proposed coded sequence pattern following the rules of Schneider [12−13]. The coding structure is a 3-layer concentric region and the center circle is divided into four parts (3/4 black, 1/4 white). Center circle area is used not only to automatically identify the region as a coded pattern and determine its location, but also to show the baseline where coding starts by means of a black-white boundary. Proposed coded sequence pattern has the following characteristics: 1) uniqueness: one coded pattern has only one corresponding code; 2) invariance to rotation and scaling; 3) easy to identify from complex background; 4) distinction between each other; 5) sufficient types. The code sequence pattern landmarks have 2^{12} types. There are still 4017 types left after removing the code which is not clear to identify. Therefore, the landmarks meet the needs of identification in the large-scale, long-range tunnel environment [14].

Scale invariance feature transform (SIFT) algorithm was employed for coarse positioning of landmarks during the mobile localization. Then the fast hough

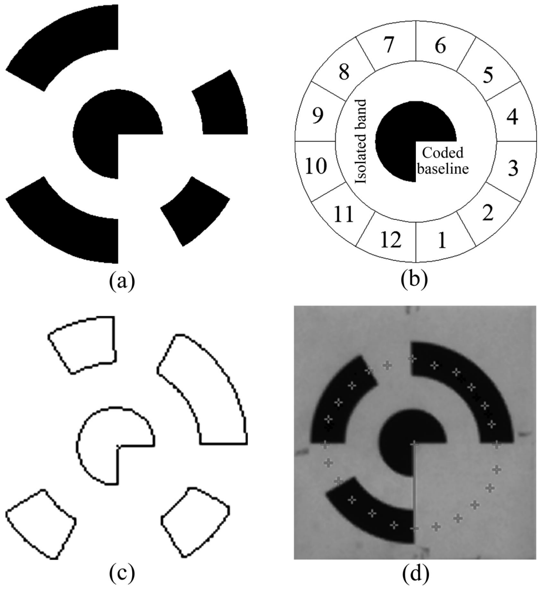

Fig. 3 Proposed coded pattern: (a) Sketch of proposed coded pattern landmark; (b) Index of coding regions; (c) Boundary tracking of coded pattern; (d) Sampling of coded pattern

transform [15] was used for identifying and acquiring the code information from landmarks quickly and accurately to achieve precise positioning. The follows are concrete steps.

1) Identification of landmarks

Firstly, extract the SIFT features from the center circle area of standard coded sequence pattern landmarks. Then match the SIFT features from standard coded pattern with the landmarks in the tunnel scene images so as to achieve the coarse position.

2) Segmentation and boundary tracking

After completion of coarse position, we can get the number of landmarks in images. Otsu algorithm is employed for calculating the segmentation threshold in order to achieve boundary tracking.

3) Finding centers of landmarks

Take it into account that the coded pattern center circle is just 3/4 circle. The fast hough transform is employed for identifying the center point $O(C_x, C_y)$ and the radius R of circle. As shown in Fig. 3, a pixel sampling method is implemented from baseline along 360° counterclockwise in order to read out the code information.

4 Registration of 3D scan data

The POSIT model was employed for finding the pose of the landmarks from images. It was assumed that not less than four noncoplanar feature points (center points of the landmarks) can be detected and matched in the images. Figure 4 shows the classic pinhole camera model.

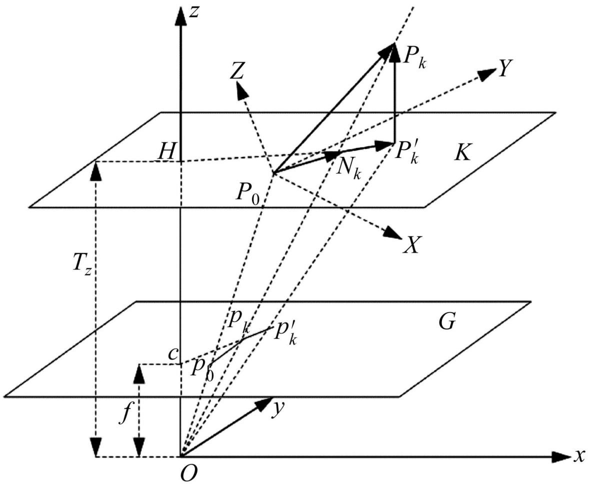

Fig. 4 Perspective projection and SOP

1) Center of projection O;

2) Image plane G at a distance f (the focal length) from O;

3) Axes O_x and O_y pointing to the rows and columns of the camera sensor, respectively;

4) Third axis O_z pointing to the optical axis.

Steps of POSIT algorithm [16] include:

1) Initialization: Write the matrix $\boldsymbol{A}$: $K\times3$; each row vector is a vector $\boldsymbol{P}_0\boldsymbol{P}_i$, compute the $3\times K$ object matrix $\boldsymbol{B}$ as the pseudoinverse matrix of $\boldsymbol{A}$;

2) $w_{k(0)}=1$, $k=1, 2, \cdots, K$, $n=1$;

3) Beginning of loop:

Compute $\boldsymbol{R}_1$, $\boldsymbol{R}_2$, $\boldsymbol{T}_z$:

(1) Compute the image vector $\boldsymbol{x}'$ with K coordinates in the form $(w_kx_k-x_0)$ and the image vector $\boldsymbol{y}'$ with K coordinates in the form $(w_ky_k-y_0)$;

(2) Multiply the $3\times K$ object matrix $\boldsymbol{B}$ and the image vectors (K coordinates) to obtain vectors $s\boldsymbol{R}_1$ and $s\boldsymbol{R}_2$ with 3 coordinates: $s\boldsymbol{R}_1=\boldsymbol{B}\times\boldsymbol{x}'$ and $s\boldsymbol{R}_2=\boldsymbol{B}\times\boldsymbol{y}'$;

(3) Compute the scale s of the projection as the average between the norms of $s\boldsymbol{R}_1$ and $s\boldsymbol{R}_2$: $s=(|s\boldsymbol{R}_1|\cdot|s\boldsymbol{R}_2|)^{1/2}$; $\boldsymbol{R}_1=(s\boldsymbol{R}_1)/s$; $\boldsymbol{R}_2=(s\boldsymbol{R}_2)/s$.

4) Compute new w_k:

(1) Compute unit $\boldsymbol{R}_3$ as the cross-product of $\boldsymbol{R}_1$ and $\boldsymbol{R}_2$: $\boldsymbol{R}_3=\boldsymbol{R}_1\times\boldsymbol{R}_2$;

(2) Compute the $\boldsymbol{T}_z$: $\boldsymbol{T}_z=f/s$, where f is the camera focal length;

(3) Compute $w_{k(n)}=\boldsymbol{R}_3\cdot\boldsymbol{P}_0\boldsymbol{P}_k/\boldsymbol{T}_z+1$.

5) If $|w_{k(n)}-w_{k(n-1)}|>$Threshold, $n=n+1$, go to 3);

6) Else output pose using values found at last iteration: the full translation vector $\boldsymbol{OP}_0$ is $\boldsymbol{OP}_0=\boldsymbol{OP}_0/s$; the rotation matrix is the matrix with row vectors $\boldsymbol{R}_1$, $\boldsymbol{R}_2$ and $\boldsymbol{R}_3$; for applications where the rotation matrix must be perfectly orthonormal, renormalize this matrix: compute $\boldsymbol{R}_3'=\boldsymbol{R}_3/|\boldsymbol{R}_3|$, $\boldsymbol{R}_2'=\boldsymbol{R}_3'\times\boldsymbol{R}_1$, and output the matrix with row vectors $\boldsymbol{R}_1$, $\boldsymbol{P}_2'$, and $\boldsymbol{R}_3'$.

The LiDAR and cameras make up the strapdown mobile positioning system and the landmarks are rigid fixed on the tunnels. Therefore, the landmarks and point cloud data have same pose parameters in each scan. Thus the proposed method can estimate the pose of point cloud data by means of calculating the translation and rotation parameters of landmarks. By doing this, the proposed method builds the 3D maps of the mine tunnels to achieve positioning the moving targets in real-time.

5 Experiment and result analysis

5.1 Experiment

Figure 5 shows the integrated experiment system with LiDAR and image sensors. Firstly, arrange the coded sequence pattern landmarks in the indoor environment, and in the same time measure the world coordinates of the landmarks' centers simultaneously, so as to establish the landmark database. Experiment system moved along the lab environment, LiDAR was scanning in the range of eighty meters and camera acquired 25 images per second containing landmarks. Onboard computer calculated the translation and rotation parameters in real time.

Fig. 5 Strapdown system integrated LiDAR and cameras

LiDAR data and images were captured in the viewpoints approximately every 5 m in the experiment. Table 1 contains the coded sequence pattern information from the landmarks obtained in the experiment, including the identification and decoding time, the image coordinates (x, y) of the landmarks, coding information (such as 100010010101) from landmarks, and the 3D coordinates (x, y, z) of landmarks acquired from landmark database. All the landmarks can be correctly decoded in the experiment.

The pose parameters of 3D scans in the viewpoints can be computed by taking the 2D image coordinates and corresponding 3D world coordinates of the landmarks centers into the POSIT model. POSIT model requires the matches of 2D image coordinates and corresponding 3D world coordinates. Mismatch will lead to erroneous results. This study employed coded pattern technology to fast access the coordinates and avoid false matches.

Five groups of LiDAR data are selected to fully test the robustness of proposed approach in the experiment. Table 2 shows the overlaps between P1 and other viewpoints (P2−P5), and overlaps between adjacent viewpoints.

We use independently acquired 3D scans from Riegl 420i terrestrial LiDAR (accuracy: ± 4 mm) in combination with a 2D ground plan map as genuine truth so as to measure derivations with six degrees of freedom (ω, ϕ, κ, X, Y, Z). Table 3 shows the translation and rotation parameters from the time-consuming ICP algorithm which is taken as reference values. Table 4 shows the errors between the pose parameters from proposed algorithm and reference values.

The proposed algorithm achieves the registration from viewpoint P1 to P5, and also accomplishes the registration between adjacent viewpoints by accurately calculate transformation parameters.

The accuracy of translation parameters calculated by proposed method is better than ±4 cm, and error of rotation parameter is smaller than 0.2°. It takes less than 60 ms to accomplish positioning:

1) Identifying and decoding the landmarks <15 ms;

2) POSIT iteration computation <15 ms;

3) Registration and mobile positioning <30 ms.

Figure 6 shows the route map by connecting the viewpoints estimated by proposed algorithm. The distance from viewpoint P_1 to P_5 is more than 20 m in the experiment. Thus the proposed algorithm can meet the needs of mobile positioning and navigation of moving targets in mine shafts and tunnels.

Table 1 Recognition of coded sequence pattern landmarks

Run time/ms	X (pixel)	Y (pixel)	Binary code	3D coordinate		
				x/cm	y/cm	z/cm
11	133.0	710.0	100010010101	−363.8	−61.8	59.1
9	933.0	672.0	001101110011	−331.7	−33.1	18.2
8	557.0	467.0	010110001110	−267.1	79.0	92.9
12	924.0	476.0	110011010001	−265.6	25.5	24.1
11	567.0	275.0	101011110101	−227.0	96.4	35.7
…	…	…	…	…	…	…

Table 2 Overlaps between 3D scans

3D scans	Overlap/%	3D scans	Overlap/%	3D scans	Overlap/%	3D scans	Overlap/%
1-2	83.1	1-4	68.8	2-3	82.6	4-5	80.3
1-3	77.7	1-5	63.0	3-4	81.3	—	—

Table 3 Pose reference of moving target from iterative ICP

3D scans	ω/(°)	ϕ/(°)	κ/(°)	X/m	Y/m	Z/m
1-2	−1.088	−0.112	51.731	−5.50	0.96	0.02
1-3	0.551	0.419	57.447	−10.69	1.87	0.08
1-4	1.984	0.481	119.261	−16.77	2.53	0.14
1-5	−0.692	0.678	−118.535	−21.05	4.24	0.16
2-3	1.432	−0.958	5.733	−2.50	4.64	0.08
3-4	0.824	−1.174	61.834	−2.72	5.47	0.01
4-5	1.482	2.238	122.148	3.58	2.90	−0.08

Table 4 Errors of pose parameters between proposed method and reference values

3D scans	$\Delta\omega$/(°)	$\Delta\phi$/(°)	$\Delta\kappa$/(°)	ΔX/m	ΔY/m	ΔZ/m
1-2	−0.031	−0.001	0.022	−0.001	−0.017	0.010
1-3	0.051	−0.082	−0.078	0.018	0.021	0.038
1-4	0.037	0.079	0.021	−0.033	−0.011	−0.025
1-5	−0.028	−0.104	0.115	−0.036	0.031	0.037
3-4	−0.031	0.018	−0.013	0.017	−0.018	0.007
4-5	0.042	−0.020	−0.016	−0.033	0.032	0.012

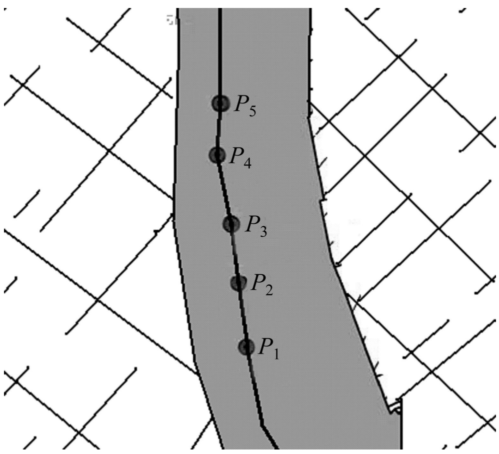

Fig. 6 Map of moving target's poses

5.2 Result analysis

By comparing the LiDAR and coded sequence pattern based mobile positioning method to the image-based MonoSLAM and LiDAR-based 6DSLAM method, proposed algorithm has the following advantages.

1) MonoSLAM algorithm localizes the targets by tracking the features from camera images. The unknown contours and complex textures may lead to failure or large positioning errors. While proposed method takes the coded sequence pattern landmarks as key points, avoiding recognition of the unknown features. It shows excellent performance in maintainability and immunity to interference in the experiment.

2) MonoSLAM algorithm takes an average of more than 20 image features for localization. So, it needs a quite large feature databases and complex computational. Proposed algorithm only needs four noncoplanar coded patterns to achieve point cloud data registration. Thus, it also has the advantages of small feature database, high speed and is easy to implement real-time positioning.

3) 6DSLAM uses the iterative ICP algorithm to register the point cloud data which takes about 5 s. While proposed algorithm employs POSIT model to calculate the pose parameters of point cloud data so as to achieve real-time positioning.

6 Conclusions and outlook

One active research area in underground mobile positioning is mapping environments by matching point clouds collected by LiDAR scanners. This study has presented a novel solution and key techniques for 3D scan matching based on initial pose parameters estimation from coded sequence pattern landmarks and POSIT model. Proposed method is to build a graph of poses by iterating scan matching.

In addition, this study has applied an experiment for evaluating the accuracy of pose estimation from 3D scans and coded sequence pattern acquired in an indoor setting. We use independently acquired 3D scans in combination with a 2D reference map as genuine truth. This enabled us to measure derivations with 6 degrees of freedom.

Much work remains to be done because some limitations of the system remain: Using LiDAR and coded sequence pattern for positioning, in areas without landmarks and lacking features, we plan to complement our system with inertial navigation system (INS). However, this switch might not be straightforward.

Future work will include three aspects. First, we will integrate LiDAR and image sensors for positioning the moving robot in the real mine shaft tunnel network environment. Second, for the problem of insufficient light in underground mine environment, further research will focus on the self-luminous coded sequence pattern technology to ensure recognition of landmarks. To this end, we plan to adapt concepts from probabilistic robotics, like explicit representations of uncertainties.

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