Quantitative Modeling and Evaluation of Urban Landmark Building Image Impact Factor Based on Computer Big Data Framework

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Abstract. This project innovates by intertwining urban identification with its context, seamlessly merging the urban identification system with natural, spatial, and historical dimensions. A distinctive urban logo system is constructed, reflecting urban characteristics. A landmark database and an attitude inference model are developed to refine robotic precision. During map generation, an amalgamation of visual and laser data produces a contextually rich laser image. Leveraging particle filtering, a novel online feature extraction technique is introduced, exploiting linear interdependencies among image components for segmentation. It selects the most discriminative sample for estimation based on calculated log-likelihood ratios, employing dual particle sets for target location approximation. Simulations confirm the method's superior tracking accuracy and robustness. The method involves harnessing two distinct methodologies to yield dual sets of particles aimed at approximating the target location. Simulation outcomes validate the superior tracking capabilities and resilience of this proposed approach.

Keywords: City landmark; city image; particulate filtration; feature selection; target tracking

1 Introduction

Landmarks are spatial concepts that play a role in identifying a specific area. Urban landmark refers to the spatial form of the city that limits its area to a certain area. As the identification and symbol of the urban space environment, as the core of public activities and gathering, it is also the support and gathering of the urban space structure. Constituting the development vein of landmark buildings. There are some orderly and internal relations between different types of urban landmark buildings, which constitute the symbol system and give the specific regional environment connotation. There are close connections between urban landmarks and urban landscape, between urban landmarks and urban environment, and these relations are interdependent, constituting the whole urban identification system. As the city's cultural heritage, it has a close relationship with the development of the whole society. The development of the city is a continuous process, and its symbol system shows diachronic and continuous in time.

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The particle filter algorithm CONDENSATION proposed in document [1] can be widely used in target tracking. The method generates a series of random samples with weights through Monte Carlo simulation, approximates the posterior distribution of the system under certain sampling conditions, and then calculates the state estimation of the system. In video images, feature selection and tracking methods are equally important, but most of the current methods build apparent modeling based on color characteristics, and remain unchanged over time, so they have a great impact on the environment, environment and other factors. In literature [2], the linear synthesis of R-values, G-values and B-values is used to obtain the candidate feature set, and the background region index between frames is weighted to obtain features with high discrimination or multiple features, and then the likelihood estimation and object tracking based on the mean shift algorithm are carried out according to these features. The algorithm is not affected by illumination, environment and other factors, and has good tracking performance for objects without object occlusion or violent movement. The drone works outdoors and is constantly moving, so the landmarks on the imaging surface change. The landmark tracking method is designed based on the fusion of image feature extraction and particle filtering.

2 Mobile Robot Repositioning Method Integrating Semantic Laser and Road Sign

Even people with GPS are likely to get lost while driving and can only navigate by road signs and landmarks. This project intends to combine semantic laser and road signs and other multi-source semantic data to obtain quantitative data such as distance and position of target objects. Semantic features such as category and name of target object are obtained by visual sensor [3]. This method can not only effectively solve the error identification and comparison caused by the factors affecting visual detection such as light and Angle[4], but also effectively reduce the influence of light and Angle on visual detection, so that it is more suitable for indoor dynamic scenes. The overall structure of the algorithm is shown in Figure 1 (the picture is quoted in Appl.Sci.2023, 13(2), 909).

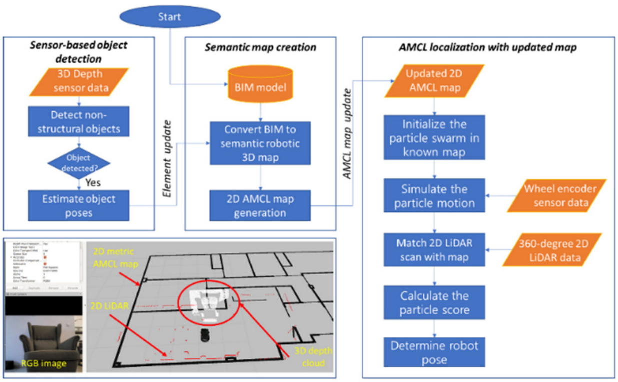

Fig. 1. Robot relocation algorithm based on semantic laser and landmark information

2.1 Establishment of Cloud Landmark Database

To ensure that only suitable objects are utilized as markers, a permission-based system is essential[5]. The Cloud Landmark Repository acts as an authorized database that enables a robot to determine its location within a specific scene by searching for a matching map. This repository is also referred to as an "alternative map." The critical step in its creation is setting stringent filtering criteria to ascertain whether a target is suitable for inclusion based on the following criteria:

The target exhibits distinctive visual characteristics such as vibrant colors, unique styles, or a distinctive logo.

The target should have a predominantly flat shape to minimize positional error from various viewing angles. Objects whose shape and position may vary are excluded to ensure data integrity[6]. Two broad categories of objects-signposts and wall images-are cataloged in the Cloud Landmark Repository. The structure of the Signpost Database System can be visualized in Figure 2.

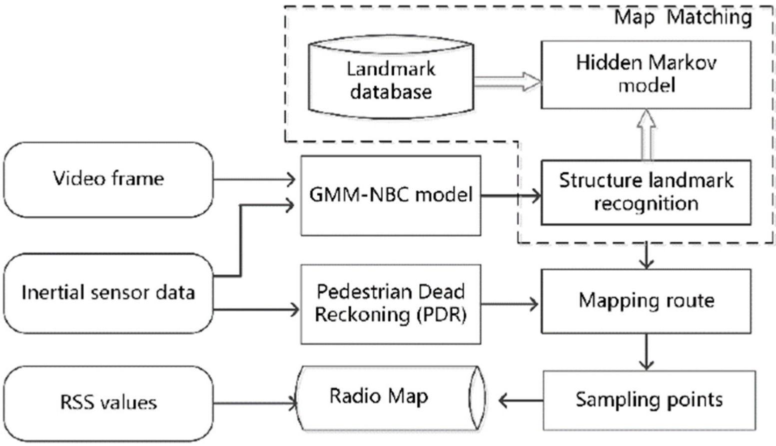

Fig. 2. Landmark database system

2.2 Construction of Efficient Roadmap Database

When constructing a map, retrieval is based on identified objects, from which appropriate landmarks are selected. Alongside the Cloud Landmark Repository, it's necessary to establish practical landmark databases, as illustrated in Figure 2. This is due to the fact that landmarks selected from the Cloud Landmark Repository may not meet practical requirements, necessitating an independent database that considers the spatial relationship between each potential landmark to choose the most suitable building for the current context. The selection process prioritizes areas that are not heavily frequented and ensures that, in maps with multiple signs, the distance between each sign isn't overly dense, considering the overall map scenario[7].

2.3 Establish Maps Corresponding to Geographical Indication Names and Coordinates of Places

An approach combining laser sensing and visual recognition is proposed to select and judge landmarks within the present scene. A mapping system corresponding to global positioning coordinates is established. The process is outlined in Figure 3. (image cited in Landmark based localization in urban environment).

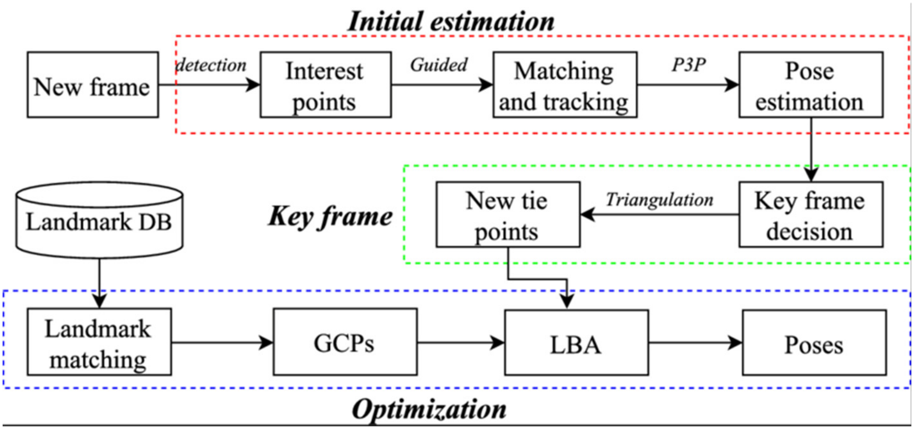

Fig. 3. Process for creating a mapping table

2.4 Obtaining Various Types of Data

Utilizing a mainstream deep learning algorithm, semantic features of the target are obtained. A comparison and analysis of existing target detection methods reveal that they fall short in terms of real-time performance and accuracy. Experiments confirm that YOLOv3-Tiny's capability in recognizing moving targets satisfies the requirements, albeit with low accuracy, particularly in identifying distant feature points in complex scenes. By incorporating a 52x52 feature scale image, the original detection rate is maintained, but accuracy improvements are not as anticipated, sometimes decreasing. The underlying network level used for extracting the 52x52 feature scale map is too low, hindering effective 52x52 feature size image extraction and reducing algorithm accuracy. Enhancements to the YOLO3-Tiny's underlying network are made, adding 52x52 layers and two 26x26 level convolutional layers, along with multi-scale feature fusion. (Figure 4 cited in the Dynamic graph convolutional network for assembly behavior recognition based on attention mechanism) and multi-scale feature fusion).

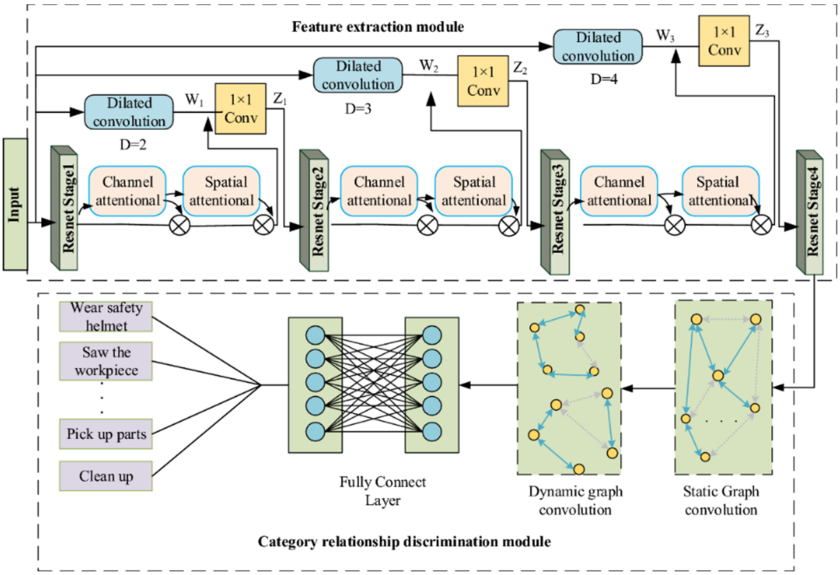

Fig. 4. Example of adding a convolutional layer

3 Implementation of Landmark Tracking Algorithm Based on Adaptive Features

3.1 Model Establishment

The motion model is shown in equation (1):

$$u_t = u_{t-1} + \lambda_t \upsilon_t, \lambda_t \propto \frac{1}{n} \sum_{i=t-n-1}^{t-1} |u_i - u_{i-1}| \tag{1}$$

υ_t is Gaussian noise with zero mean unit variance. The color histogram has a good ability to characterize the rotation, deformation, occlusion and other features of the object. Generally, pixels far away from the object are easy to be disturbed by occlusion and background pixels, and the closer the pixel is to the object, the higher its credibility [8]. By adjusting the weight of the color histogram, the shape of the object can be better reflected. Let the central coordinate of the target be h, the histogram quantization series be n, and the pixel coordinate in the tracking area be $\{u_i\}_{i=1,2,\cdots,N}$, then the color histogram distribution of the target can be expressed as $q = \{q_\sigma(h)\}_{\sigma=1,2,\cdots,n}$, and:

$$q_\sigma(h) = g\sum_{i=1}^{N} i(\| \frac{h-u_i}{l} \|^2)\zeta(b(u_i)-\sigma)$$
$$g = \frac{1}{\sum_{i=1}^{N} i(\| \frac{h-u_i}{l} \|^2)} \tag{2}$$

l is the kernel bandwidth; ζ is the Kronecker function; $i(\| u \|^2)$ is the kernel function:

$$I(u) = i(\| u \|^2) = \begin{cases} 1-\| u \|^2 & if \ \| u \|^2 < 1 \\ 0 & otherwise \end{cases} \tag{3}$$

The similarity between histogram $q = \{q^{(i)}\}_{i=1,2,\cdots,n}$ and $w = \{w^{(i)}\}_{i=1,2,\cdots,n}$ whose quantization series is n can be measured by the Bhat tach array distance $s(q,w)$:

$$s(q,w) = \sqrt{1-\rho(q,w)} \tag{4}$$

$\rho(q,w)$ is the Bhattacharyya coefficient, $\rho(q,w) = \sum_{i=1}^{n} \sqrt{q^{(i)} w^{(i)}}$. Further, the likelihood function can be obtained as $q(c_t \mid u_t) \propto \exp(-\omega s^2(q,w))$. ω is the adjustment parameter. It can be seen that the smaller $s(q,w)$ is, the higher the similarity between the two histograms is, and the greater the weight of the corresponding particle is.

3.2 Likelihood Image Acquisition

First, the candidate feature set is established in the RGB color space:

$$G \equiv \{\omega_1 R + \omega_2 G + \omega_3 B \mid \omega_i \in \{-2,-1,0,1,2\}\} \tag{5}$$

After eliminating redundant features, only 49 distinct features are retained. For A feature, let l_o represent the histogram of the target region, l_b represent the histogram of the background region, and i represent $i-bin, q(i), w(i)$ of the histogram as the corresponding quantity of $l_o(i), l_b(i)$ after the normalization of l_o, l_b, then the differentiation degree of the feature to the background target can be judged by equation (6) :

$$VR(R;q,w) = \frac{\text{var}(R;(q+w)/2)}{\text{var}(R;(q) + \text{var}(R;(w)} \tag{6}$$

$\mathrm{var}(R;i)$ is the variance of R obtained from the probability distribution:

$$\mathrm{var}(R;i) = \sum_i i(i)R^2(i) - \left[\sum_i i(i)R(i)\right]^2 \tag{7}$$

$R(i)$ is the log-likelihood ratio of $q(i)$ and $w(i)$:

$$R(i) = \lg \frac{\max\{q(i), \varphi\}}{\max\{w(i), \varphi\}} \tag{8}$$

φ minimum value greater than 0 set to prevent the denominator from being 0. The higher the value of $VR(R;q,w)$, the better the ability of the feature to distinguish between the target and the background. Figure 5 is the likelihood image in the corresponding tracking window obtained by some features.

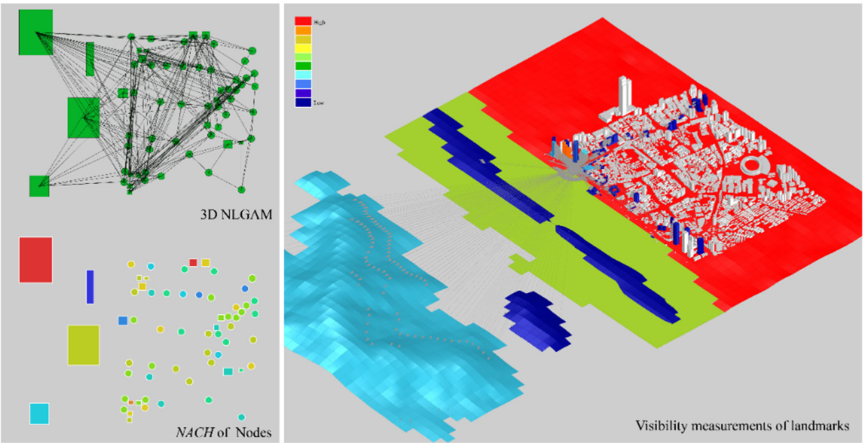

Fig. 5. Likelihood images obtained from partial features

4 Algorithm Implementation

With the increase of the number of particles, the target can be tracked better, but at the same time, the operation speed is increased and the performance is decreased. In addition, it takes a lot of time to build the bar chart. In the fields of gesture tracking, multi-object tracking and integrated learning, scholars at home and abroad have done research on this. In this method, the average offset algorithm is introduced to achieve the global optimal location of the target region, reduce the calculation amount caused by too much weight, and improve the target tracking effect. In addition, the localization of multiple points in the large likelihood domain is also greatly improved. After the average displacement, the particles aggregate towards the target region. However, from an overall point of view, because the average movement can lead to the loss of some local minima, this project proposes to combine a series of particles with non-average movement for positioning. When the light changes, the weight of each particle becomes lower, so the tracking of the target is very sensitive. Therefore, the weight threshold ζ_{thresh} is defined, and the weight threshold is used to monitor the motion of particles, thus effectively limiting the influence range of particles and reducing the influence of useless particles.

Through the comparative analysis of several sets of images, the obtained results are consistent with those of mean shift and particle filter algorithm. At the start frame, the reference mode of the tracked object is manually selected. Each method uses 20 particles, while particle filtration uses 120 particles. This project takes the indoor scene as the background, and verifies the brightness difference of the method in different scenes by simulating the lighting conditions in different scenes. The results of the tracking are shown in Figure 6 and Table 1 (image cited in Buildings 2023, 13(4), 1024). In the process of average deviation, the trajectory window will shift continuously with the change of illumination. However, when using this method, there are some problems such as offset or missing tracking window, but the particle set has a large space in one image and can be located in several subsequent images. Because the method can dynamically adjust the image during tracking, and reduce the influence of the change of light on the image quality, there will be no window shift and no missing target phenomenon in the image, and the image can be accurately tracked at any time.

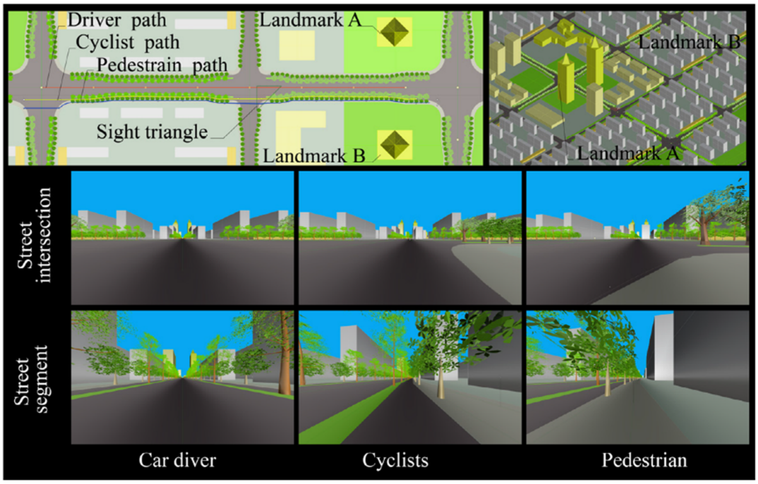

Fig. 6. Tracing results

Table 1. Tracking data statistics

Algorithm	Particle population	Abscissa error per pixel	Ordinate error per pixel
Textual method	21	3.02	3.85
Particle filter	125	5.00	5.31
Mean shift	-	Target loss occurred	

5 Conclusion

In the construction of urban spatial pattern, the effective integration of sign system and environmental context is very important for functional optimization. For unmanned aerial vehicle (UAV) technology, an advanced computational method based on particle filter algorithm is proposed to classify and analyze data input from multiple sensors. Specifically, the algorithm targets a number of key data points, enhances the distinction between the target and the background, and minimizes lighting and rotation interference. By adopting the motion-based optimization technique, the target particle subset is strategically moved to the local minimum point, thus improving the tracking accuracy and computational efficiency. This approach not only advances drone technology, but also contributes to smarter urban planning through data-driven decision-making.

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