A Bio-Inspired Goal-Directed Visual Navigation Model for Aerial Mobile Robots

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Abstract

Reliably navigating to a distant goal remains a major challenge in robotics. In contrast, animals such as rats and pigeons can perform goal-directed navigation with great reliability. Evidence from neural science and ethology suggests that various species represent the spatial space as a topological template, with which they can actively evaluate future navigation uncertainty and plan reliable/safe paths to distant goals. While topological navigation models have been deployed in mobile robots, relatively little inspiration has drawn upon biology in terms of topological mapping and active path planning. In this paper, we propose a novel bio-inspired topological navigation model, which consists of topological map construction, active path planning and path execution, for aerial mobile robots with visual landmark recognition and compass orientation capability. To mimic the topological spatial representation, the model firstly builds the topological nodes based on the reliability of visual landmarks, and constructs the edges based on the compass accuracy. Then a reward diffusion algorithm akin to animals’ path evaluation process is developed. The diffusion process takes the topological structure and landmark reliability into consideration, which helps the agent to construct the path with visually reliable nodes. In the path execution process, the agent combines orientation guidance and landmark recognition to estimate its position. To evaluate the performance of the proposed navigation model, a systematic series of experiments were conducted in a range of challenging and varied real-world visual environments. The results show that the proposed model generates animal-like navigation behaviours, which avoids travelling across large visually aliased areas, such as forest and water regions, and achieves higher localization accuracy than navigating on the shortest paths.

Keywords

Bio-inspired navigation · Active navigation · Topological navigation · Aerial robots

1 Introduction

Reliably navigating to a distant destination is of great importance for autonomous systems, but it still remains a challenge in the field of robotics. Currently, most deployed robotics navigation models are passive in the sense that the agent only estimates the navigation states based on the observed information, and has little considerations on how future observations can affect the state estimation uncertainty. However, animals show superb active navigation ability, where they can evaluate and decide future actions to reach a distant goal safely.

World representation and path planning are the basis for active navigation. Extensive research has revealed that place cells in the hippocampus support retrieval of the past spatial memory to simulate the future [1–4], however, it remains controversial about the neural activation mechanism. Recent observations of the place cell co-firing activity have inspired the assumption that the place cells may encode the environment as a topological template [4–6], where nodes represent the places in the physical space and the topological edges refer to the spatial relations between them. Within this assumption, the hippocampus can simulate future paths by retrieving the topological structure. Analyse of homing pigeons’ routes also supports the topological navigation mechanism [7, 8]. Released homing pigeons show loyalty to their routes, which are consists of a sequence of familiar landmarks. Such landmarks can be regarded as topological nodes and their topological connections between them formed the graph-like homing routes. Navigating to a distant goal by using a graph-like sequence of familiar landmarks is also observed in insects [9, 10]. The formation of such topological cognition appears to
relate to an array of stimuli, such as visual cues, head direction and path integration, as hippocampal place cells respond to these stimuli [11–13]. But the mechanism about how the topological spatial representation is formed remains largely unknown. Another unsolved question is how animals evaluate and decide to navigate a path. The evaluation of possible future paths is argued to be processed in the prefrontal cortex (PFC) [14, 15]. However, the factors that lead to the different rewards of different paths are largely unanswered.

Topological navigation approaches are also widely deployed in mobile robots, especially in long-range navigation, due to its simplicity [16–21]. Representing the spatial space as a topological graph helps to capture the high-level conceptual understandings of an environment. For instance, city roadmap can be described as a topological graph, where the nodes refer to road segments and the edges describe the intersections that connect the road segments [22, 23]; an indoor environment can also be interpreted as a topological map, where the nodes represent different rooms and the edges describe the passageways connecting the rooms [24]. Path planning with a topological map can be performed with graph search techniques, which outputs a path consists of a sequence of adjacent nodes. In the navigation process, the robot follows the nodes along the planned path to reach the goal.

There are two premises for a successful topological navigation. Firstly, the onboard navigation system should have the ability to guide the robot travel across two adjacent nodes. Path integration and compass orientation are commonly used methods that provide cross-node guidance. However, most deployed topological mapping systems focus on building the edges to represent the physical connections (such as intersections or doors), relatively little attention has been paid on interpreting the cross-node reachability in topological mapping. This brings in the risks that the agent could deviate the planned path and fall into unknown areas due to path integration drifts or compass errors. The second premise is that the robot needs to have an awareness of its located node. It is only when the robot recognizes its located nodes, can it make the right movement targeting to the next one; this recognition capability is usually accomplished by a landmark recognition or place recognition technique [25, 26]. However, landmark recognition techniques are limited by perceptual ambiguity. This leads to an interwoven problem: on the one hand, landmark recognition determines if a planned path can be executed successfully; on the other hand, the planned path determines the landmark recognition ambiguity to be encountered in the future. While conventional passive navigation approaches focus on estimating the located nodes based on the obtained sensory information, an active navigation method takes future uncertainty into path planning to reduce navigation failure possibility.

Animals show impressed active navigation capability in dealing with navigation uncertainty, e.g. place cells show preference to some special locations [27, 28] and pigeons follow their familiar landmarks [7, 8]. Though there are debates about the neural and ethological evidence in animal’s navigation mechanism, the current research still contains some inspirations to address the robotic navigation challenges. In this paper, we propose a novel topological navigation model for aerial mobile robots to generate animal-like active navigation behaviours (Fig. 1). The model provides three key robotic navigation capabilities drawn from biological inspiration: topological map generation (including self-assessment of map quality and reliability), active path planning and navigation strategies for executing the route.

More specifically, the model uses compass orientation aided path integration (PI) and visual landmark recognition to perform topological navigation. A novel method is proposed to assess the landmark recognition reliability, which is further used to partition the space into node areas at different levels of reliability. The edges between the nodes are built based on the onboard compass accuracy to guarantee the cross-node reachability. Based on the topological map, we propose a reward diffusion process to assign each node a reward score based on the graph structure and node reliability; following this, a reward-based heuristic path planning algorithm is proposed. To execute the path, the navigation model combines a compass orientation aided PI component with a visual landmark recognition technique. While most topological navigation models are used in ground mobile robots [18] and lack considerations in node recognition reliability and cross-node reachability, this paper presents a comprehensive active topological navigation system for aerial mobile robots. The main contribution of this paper is as followed:

1. We propose to assess the recognition reliability of each landmark and then construct different topological nodes to describe the regions that contain the landmarks at different reliability levels.
2. We build the topological connections based on the compass accuracy to guarantee the cross-node reachability.
3. We develop an active path planning method which uses visually reliable nodes to construct paths to distant goals.
4. We conduct extensive experiments in different visual environments with challenging visual variation and ambiguity. We also compare the proposed active topological navigation method with a conventional passive navigation method and the shortest path navigation method, which are widely deployed in robotic navigation systems.

The proposed active topological navigation model generates reliable paths to distant goals, which avoid using landmarks in visually ambiguous areas, such as water regions, mountain areas and grassland (Fig. 1).

The paper proceeds as follows: Section 2 reviews the related research in biology and robotics. Section 3 presents the
detailed approach. The experimental setup and results are shown in Section 4 and 5, with discussion in Section 6.

2 Background

This section briefly reviews the research on topological navigation both in the field of biology and robotics.

2.1 Topological Navigation in Biology

Animals’ superb navigation capability relies on their ability to create a spatial map in their brain and the ability to retrieve the spatial memory for decision-making. The hippocampus place cells in the brain are considered to play a critical part in spatial memory and memory for events. Electrode recordings have revealed that neurons in the hippocampus fire at specific locations, and hence are known as “place cells” [27, 28]. However, the role of the place cells in spatial cognition and navigation is still controversial. Place cells appear to respond to a series of stimuli, such as visual clues, self-motion and goal planning [30, 31]. Recent study has also revealed the co-firing activity of place cells [32, 33]. These observations have inspired that the hippocampal place cells may represent the spatial environment as a topological graph, where the topological nodes refer to place fields and the topological edges demonstrate the connectivity between the places [4–6, 34]. The topological template may be re-capitulated during the ‘off-line’ hippocampal replay events, where the place cells show re-activation of spatial sequences [6]. The place cells have also been observed to sweep ahead of an animal located at a choice point, leading to the hypothesis that the topological structure could support path planning and decision making as well [35]. Recent observations found that the online activation of place cells in human brain also correspond to the city roadmap topological structure. Moreover, the activation of the lateral prefrontal cortex (PFC) correlates with the demands of a breadth-first search at detours; this suggests that humans hippocampal place cells also captures the topology of the environment for navigation implementations [4].

Capturing the topological structure of the environment is useful for active navigation; animals can actively retrieve and evaluate the topological graph to find the path to a distant place. Though the neural evidence of topological navigation has enriched during the past years, the detail of the neural basis for topological navigation is still largely unanswered. For instance, it is still unclear how animals evaluate potential accessible paths for decision making. The PFC is a candidate region where evaluation takes place as supported by the evidence that damage to PFC impairs planning and problemsolving [14, 15], but the evaluation mechanism remains unveiled currently.
Research on pigeon’s homing behaviours also supports the topological navigation hypothesis [7, 8]. The GPS tracks have shown that thought one pigeon’s homing routes are different after each release at the same location, it shows loyalty to follow some specific areas. Such areas form a graph-like route stereotypy, as shown in Fig. 1, indicating that the pigeon has an awareness of the topological connections between the places. Further inspections on the preferred areas show that they are often observed at distinctive boundaries in the underlying landscape, such as boundaries between village and forest; this is consistent with the neural observations that visual clues contribute significantly to place cell activations [13, 36].

Moreover, experiments have shown hippocampal lesions to pigeons can affect their landmark recognition ability, which indicates the hippocampus is also involved in pigeon’s active topological navigation behaviours [37]. Actively using a set of preferred landmarks in navigation have also been observed in insects [9, 10]. The landmarks that define insects’ routes can be visual, olfactory, textural and magnetic signatures that are uniquely associated with them [10]. Such landmarks are of significance for active navigation. Evidence found that, even in unfamiliar terrains, ants rely on landmark guidance and do not completely fall back onto path integration [9, 38, 39]. Similar to pigeons’ homing routes, the landmarks defining the routes can be regarded as topological nodes and the connections between them make up the graph-like routes.

### 2.2 Topological Navigation in Robotics

Topological navigation has also been extensively studied in mobile robots [18, 25]. By defining possible places in the world as nodes and passageways between these places as edges, the navigation process can be regarded as following edge segments to the goal. Associating physical places and paths to abstract nodes and edges is a key step in topological mapping. One deployed approach is to associate each node with a keyframe or snapshot [16, 17, 24], where each keyframe captures the appearance of a place. A new node can be added into the graph whenever the newly obtained image is distinctive to the existing ones. As the places are indeed described by camera images obtained at the exploration stage, the edges can be constructed by linking up the places in consecutive keyframes. Such topological information has been used to augment the place recognition performance in a robot’s localization system [40, 41]. However, linking up the consecutive camera frames only captures the topology of the explored paths, thus the robot can only replay the historical paths. An alternative map construction strategy is to partition the environment based on the underlying nature topology. For example, the physical space can be partition into node regions according to landmark co-visibility [42] or space convexity [19]. Meanwhile, the edges can be constructed by linking up the adjacent regions. Another topological navigation example that makes use of nature topology is the roadmap-based navigation methods [22], where nodes refer to road segments and edges interpret the intersections. Utilizing the underlying topology to construct the topological map might be meaningful in human point of view, e.g. each room or road segment makes up identical nodes, but requires an accurate metric map of the environment for space clustering, such as metric grid map [19, 42] or roadmap [22]. With the developments in computer vision, some research proposed to associate a region with the same semantic meaning to a node [24, 43]; such topological maps help to obtain high-level understandings of the environment, for example, an indoor navigation task can be interpreted as passing across the living room to reach the kitchen.

Topological navigation methods that draw inspirations from biological research have also been proposed to address the robotic navigation challenges [44–50]. The core of these models is a place cell map or a landmark tree graph, which imitate the place cell’s spatial encoding pattern. However, the places assigned to the nodes refer to abstract areas or highly distinctive artificial landmarks in small-scale environments; this makes most of the existing bio-inspired topological navigation models unsuitable for real-world robotic applications, where perfect data association is not available.

While most existing methods focus on applying topological navigation models to ground vehicles [19, 22, 40–42], relatively little attention has paid on how to deploy topological navigation to aerial mobile robots. This might stem from that the open aerial environments lack nature topology for use. Thus, roboticists have to design proper criterions to construct the nodes and edges in a topological map. One significant advantage of topological navigation is that it simplifies the path planning process, which generates a path consists of a sequence of nodes. The key to executing the planned path is that the agent can recognize itself being at a certain node on the path and can reach the next node successfully. However, currently deployed topological maps address more on splitting the space into subregions, but less on how the node recognition and cross-node reachability uncertainties can be interpreted in the mapping stage.

### 3 Approach

This section presents our approach in detail, which consists of three components: topological map creation, active path planning and path execution. The first component constructs the topological map by partitioning the physical space into topological nodes based on visual landmark reliability and then connecting the node areas based on compass accuracy. The second component is processed in the topological space, where a reward diffusion process is used to evaluate the
reward of each node and guide active path planning. The third component describes the path execution mechanism, which is a combination of visual landmark recognition and compass orientation aided path integration. Figure 2 shows an illustration of the proposed method.

3.1 Topological Map Creation

Animals show a tendency to follow some preferred areas in goal-directed navigation, e.g. homing pigeons follow familiar landmarks [7, 8, 51] and hippocampal place cells activate at some specific locations [27, 28]. Such specific areas are considered to be highly recognizable so that animals can perform position calibration there confidently. Reliably recognizable landmarks are also very important for mobile robots. Recognizing a landmark can reduce position drifts caused by path integration, as exemplified by loop closure or place recognition in a SLAM system [17, 25], but falsely recognizing a landmark can be catastrophic for a mobile robot as it relocates to an incorrect position. While animals can evaluate landmark reliability and actively retrieve familiar landmarks for navigation, relatively little research has addressed how to evaluate and map reliable landmarks for robotic applications. In order to learn animal-like spatial representations to address robotic navigation challenges, we propose to constitute a topological map with reliable landmarks for visual place recognition.

Before the topological map creation, the environment is divided into small areas. Each small area is regarded as a landmark, which can be sensed by an aerial downward-looking camera.

3.1.1 Visual Landmark Reliability Assessment

Reliable visual landmarks should be distinctive to other landmarks. When the distribution of the reliable visual landmarks is available, the navigation system can actively inform the agent to move forward to these areas to calibration position by utilizing a visual place recognition approach [25] or other techniques. Some research has addressed extracting reliable local features within an image [52–55]. However, we focus on finding reliably recognizable landmarks throughout the whole environment.

The proposed assessment component assigns a reliability score to each landmark by analysing the visual features extracted from historical landmark images. In detail, for each landmark, one historical image is collected to constitute a reference image database. Each image in the database is then described as a 256-dimensional MAC (Maximum Activation of Convolutions) feature [55–57], which is generated by a trained neural network consists of a series of convolutional layers. Previous work has demonstrated that MAC features are robust to severe appearance variations and achieve...
impressed place recognition performance [55, 57]. The distinctiveness of the visual features is measured by the feature distance, therefore a landmark’s reliability score is modelled as the minimal L2 norm distance between its historical image’s feature and the features obtained at other landmarks as:

$$s_i = \arg \min_{j \in h(i)} \left( ||f_i - f_j|| \right)$$

(1)

where $s_i$ is the obtained reliability score of the $i$-th landmark and $f_i$ is the feature descriptor of the landmark’s historical image; $h(i)$ is a set of indices referring to the landmarks that have no overlap areas with the $i$-th landmark area. Eq. (1) demonstrates that landmarks with higher reliability have larger margins to other landmarks in the feature space.

### 3.1.2 Associating Topological Nodes with Landmarks

Recent evidence supports the hypothesis that the hippocampus encodes the layout of the environment as a topological map, where each node is associated with a unique area in the environment [4–6]. Based on the reliability scores assigned to the visual landmarks, there are two possible ways to constitute the topological nodes: (i) each node associated with a single landmark or (ii) each node contains a set of nearby landmarks. The former method results in a topological map with fixed small-scale nodes, where the agent could fail to hit a desired distant node due to path integration drifts. However, animals, especially avian species, show the ability to travel across distant waypoints [7, 8]. Therefore, we associate each node with a set of landmarks, where each node refers to a circular area satisfying: 1) has a radius larger than a radius threshold and 2) all landmarks located in that circle have a reliability score higher than a predefined threshold. In the following, we use the term node reliability score to refer to the reliability threshold in building the node. Then a topological node can be described as:

$$p_i = [s, x, y, r, \text{Ind}]$$

where $s$ is the node reliability score, $x, y$ is the centre of the node area, $r$ is the radius of the node area and $\text{Ind}$ is a set of indices referring to the landmarks located in the node area.

Setting a high-reliability threshold can exclude unreliable landmarks, thus the constructed nodes are highly reliable for place recognition; however, this can also lead to low coverage of the physical space, which in turn leads to low connectivity between them as they are distant from each other. On the other hand, setting a low-reliability score can have sufficient coverage of the physical space, but the constructed nodes are of low reliability for place recognition. To build a topological map that has sufficient coverage of the physical space while also distinct the high-reliability and low-reliability regions, we propose to construct the topological nodes at multiple reliability levels; this is achieved by setting multiple reliability thresholds and applying the thresholds in descending order. As the constructed nodes have overlapping areas, we also sparse the heavily overlapped nodes for brevity. In detail, the nodes that include more than 50% landmarks from a larger node or from a more reliable node are discarded.

### 3.1.3 Constructing Topological Edges

For ground mobile robots, topological connections mostly refer to the traversable free space (such as doors [24] and road intersections [22]) or the adjacency between the node areas [58]. However, from the navigation perspective, the topological links should indicate the agent’s reachability when traveling across two nodes; otherwise, when the agent executes a planned path, which consists of a sequence of nodes, it might fail to reach the targeted node area. Here, we focus on constructing the topological links of an open environment for aerial mobile robot applications. We propose to build the topological adjacency based on the onboard compass accuracy. In detail, the graph topology is represented by a matrix $W$, where each row represents the edges starting from a unique node. Each element in the matrix is determined as:

$$W_{i,j} = \begin{cases} 
1, & \text{if } \sin(\theta) < = \sin(\alpha_{i,j}) \\
0, & \text{otherwise} 
\end{cases}$$

(2)

where $\theta$ is the compass accuracy (in this paper the compass accuracy is defined as the maximum orientation error) and $\sin(\alpha_{i,j})$ is computed as:

$$\sin(\alpha_{i,j}) = \frac{r_j}{r_i + L_{i,j}}$$

(3)

where $L_{i,j}$ is the distance between the centre of the i-th and j-th node area. Figure 3 shows the geometric relationship between the two connected nodes. When $W_{i,j}$ is true, it is guaranteed that if the agent starts at any point in the i-th node, it can reach the j-th node by compass orientation guidance only. Otherwise, the agent could miss the j-th place field when starting at some positions in the i-th place field. Some mobile robots are also able to sense translation movements from visual odometry or other techniques. However, it is the orientation accuracy that determines whether an aerial robot can ‘hit’ the desired place field or not.

![Fig. 3 The geometric relationship between the two connected nodes](image-url)
3.2 Active Path Planning

While the physical space is interpreted as a topological graph, path planning in the topological space is indeed a process of searching a sequence of adjacent nodes from the starting node to the destination node. Graph search techniques have been widely used in path planning; meanwhile, hippocampal place cell activations indicate that human also simulates future paths in a graph-search fashion [4]. However, the mechanism that how the brain evaluates and chooses different graph paths are largely unveiled. Based on the observations that pigeons use distinctive landmark in homing [7, 8, 51], we proposed to utilize node reliability to guide the path planning; this graph search method also helps to deal with the landmark recognition uncertainty. As the edge construction approach guarantees that the robot can travel across two adjacent nodes, one major navigation uncertainty lies at the node recognition process. If the robot fails to recognize a node along the planned path, it will deviate from the path and fall into unknown risks.

The proposed path planning method consists of two steps. The first step is a reward diffusion process, which generates a reward score to each node based on the graph structure and the node reliability; the second step searches the graph towards the optimal reward to obtain a path to the destination.

3.2.1 Reward Diffusion

Evidence from neural science suggests place cells can respond to food and other rewards; avian also show a tendency to draw high reward to landmarks with salient landscape structures [7, 8, 51]. Though it is still unclear in detail about how animals reward different paths, we propose the reward diffusion is related to the topological graph structure and node reliability.

In order to utilize reliable nodes to reduce the navigation uncertainty, the proposed reward diffusion method generates a gradient descent reward score from the destination node to the starting node. The proposed reward diffusion method is similar to [59], where reward scores decrease as the graph depth increases. However, the existing reward diffusion method assigns the same reward score to the nodes at the same depth, which lacks the considerations in distinguishing the nodes with different reliability. Here we develop a hierarchical reward diffusion method based on [59], which not only generates descending rewards as graph depth increases but also assign higher rewards to higher reliability nodes that are at the same graph depth.

The idea of the proposed method is to select high-reliability nodes to diffuse the reward signal at first; it is only when the topological connections among the selected nodes have no accessible paths to propagate the reward signal, that the low-reliability nodes are added into the diffusion process. By doing so, for the nodes at the same depth, the nodes with higher reliability receive higher reward scores. Thus, the agent can actively pick reliable node to build up future paths at each decision-making point.

In detail, the reward diffusion process first initials the destination node with reward value 1 and all others 0. The reward vector \( r(0) \) then can be expressed as:

\[
 r_i(0) = \begin{cases} 
 1, & \text{if } p_i \text{ is the destination node} \\
 0, & \text{otherwise} 
\end{cases}
\]

The next step selects the nodes above a reliability threshold for reward score propagation. Suppose that all the topological nodes are categorized to \( M \) different reliability levels (in descending orders) as described in Section 3.1.2, the first diffusion step sets the reliability level index as \( m = 1 \), which means only the nodes with the highest reliability are included in the diffusion. The reward scores are then updated as follows:

\[
\begin{align*}
 a(k) &= r(k-1) \\
 \alpha(k) &= (k + 1)^{-1} \\
 a(k) &= H(a(k-1) \cdot W_m) \\
 r_r(k) &= \max(\alpha(k) \cdot a(k), r_r(k-1))
\end{align*}
\]

where \( k \) represents the \( k-th \) diffusion step; \( W_m \) is the topology between the nodes above the \( m-th \) reliability level, which is obtained by only remains the corresponding rows in \( W \), and set all other row values to zeros; \( H(\cdot) \) is a Heaviside step function with \( H(0) = 0 \).

Equation (4) only updates the reward scores of the nodes above the settled reliability threshold. When \( r_r(k) = r_r(k-1) \) and \( m \neq M \), the diffusion fails to update the reward scores due to the limited connections between the selected nodes. Under this circumstance, the diffusion algorithm increases the reliability level index by 1, as \( m = m + 1 \) to lower the reliability threshold, and reuse Eq. (4) to update the reward score. Once \( r_r(k) \neq r_r(k-1) \), it means at least one node’s reward score is updated benefit from the enriched topological connections, and then the index is reset to \( m = 1 \) to search high reliable nodes for reward diffusion. When \( r_r(k) = r_r(k-1) \) and \( m = M \), all nodes that have accessible paths to the goal have been rewarded. Then, the reward diffusion process terminates under this condition.

The above hierarchical process preferred to use high reliable nodes to propagate the reward signal, which in return assign higher reward scores to the nodes with higher reliability. The detailed reward diffusion algorithm is presented in Table 1.

3.2.2 Path Planning

In most cases, the destination node is not directly connected to the starting node. Thus, the agent has to decide how to organize the nodes to obtain a path to the distant goal. As all the nodes are rewarded, we propose to use the reward signal to guide path planning. In detail, the agent picks the adjacent node with the highest reward score as a sub-goal until the destination node is reached.
At this point, a path to the destination node is defined by a sequence of adjacent nodes in the topological space, but it needs to be translated into a path in the physical space for real applications. We accomplish the translation by linking up the consecutive node areas with line segments. In detail, the first line segment links from the initial position to the center of the second node. Then, the following line segments link the centers of two consecutive node areas. Finally, the end of the last line segment links to the destination landmark. Figure 4 illustrates the generated path in the physical space.

The advantage of using the proposed path planning method is to reduce the long-range navigation uncertainty by setting a series of sub-goals at visually reliable areas. When the agent is incapable of reaching a distant destination area due to orientation or other errors, it can divide the navigation task into several sub-tasks where the reachability between two consecutive node areas is guaranteed, and each node area contains reliable landmarks for landmark recognition.

### 3.3 Path Executing with Compass-Aided Path Integration and Visual Landmark Recognition

This section presents the path execution mechanism, which is a combination of compass aided PI and visual landmark/place recognition; such a combination of orientation guidance and landmark calibration is shown in extensive species [7, 8, 60, 61] and also deployed in many mobile robots’ navigation systems [62–65].

In practical, the path integration component is mostly performed with an inertial navigation system, visual odometry or

| **Reward Diffusion Algorithm** |
|---|
| **1** **Input:** Node reliability \(\{s_i\}_N\) |
| Descending order node reliability levels \(\{s_{thr,m}\}_M\) |
| Topology matrix \(W\) |
| Initial reward score \(r(1)\) |
| Initial reliability level index \(m = 1\) |
| Reward diffusion step counter \(k = 1\) |
| **2** **while** true |
| **3** \(k = k + 1\) |
| **4** Select the node for reward diffusion: \(I_m = \text{find index}\{s_{thr,m} \leq \{s_i\}_N\}\) |
| **5** Remain \(I_m\) row in \(W\) and set other rows to zeros to obtain \(W_m\) |
| **6** Reward update as in Eq.(4) |
| **7** if \(r_i(k) = r_i(k - 1)\) and \(m \neq M\) |
| \(m = m + 1\), **continue** |
| **9** elseif \(r_i(k) = r_i(k - 1)\) and \(m = M\) |
| **10** **break** |
| **11** **Output:** reward score vector \(r\) |

Fig. 4 Illustration of the proposed path. The proposed method firstly defines the path to the goal as a sequence of nodes. The corresponding path in the physical space consists of a series of line segments linking up two consecutive node areas.
other techniques. To constrain the orientation drifts, a compass is usually used to obtain an integrated path integration component [62, 63, 65], in which the orientation drift can be restricted to a certain level. As the main scope of this paper is the proposed active navigation model, we will not inspect the details of the path integration component but use a virtual compass aided PI to provide motion estimation.

As the topological edges are built to depict the reachability under compass orientation, it is guaranteed that the agent can always travel across two adjacent nodes. However, for most cases, there are more than two nodes along the planned path. Thus, the agent needs to change its moving direction at each node to target at the next node. The key to updating the orientation guidance is to rightly inform the agent of its current position. While path integration suffers from position drift, we propose to use visual landmark recognition to calibrate the position from prior landmark experience. In detail, the position calibration process compares the images obtained from a downward-looking camera to the historical image database (which is also used in Section 3.1.1), where all reference images have a position label from prior experience. Once the system deems the current obtained image is captured at a known position, the agent is then relocated to that landmark position. The landmark recognition is processed by comparing image features as:

\[
i_{\text{rec}} = \arg \min_{i \in [1,N]} \left( \| f_q - f_i \| \right)
\]

where \(i_{\text{rec}}\) demonstrates the recognized landmark index; \(f_q\) is the visual descriptor of the camera image and \(f_i\) is the visual descriptor of the \(i\)-th landmark image in the database; \(N\) is the total number of images in the database.

The visual place recognition component can provide accurate position estimation regardless of the travelled distance and time. However, the landmark appearance variations, such as illumination, viewpoint and other variations, can cause false recognition results. To improve the place recognition capability, we filter out the recognized landmarks that are beyond the path integration uncertainty range. Mostly, the accuracy of the path integration accuracy is characterized as a ratio to the travelled distance, which can be estimated from a calibration process. Suppose that, the error ratio of the path integration component is \(\rho\), and the travelled distance from the last position calibration is \(L\), we filter out the place recognition results that satisfying:

\[
\rho \cdot L \leq \| L_{\text{rec}} - L_{\text{PLI}} \| \leq C13
\]

where \(L_{\text{rec}}\) is the position of the recognized landmark and \(L_{\text{PLI}}\) is the position estimated by path integration at the current time \(t\). Once a recognized landmark is accepted by the navigation system, the agent is relocated to that landmark position. The diagram of the path execution method is shown in Table 2.

### 4 Experimental Setup

To test the proposed navigation model, a series of simulation experiments were conducted with real-world aerial images obtained at different visual environments.

#### 4.1 Testing Datasets

Three datasets were used to evaluate the proposed topological navigation approach: the Coast dataset, the Mountain dataset and the Village dataset. These three datasets consist of diverse visual environments including urban, rural and coastal regions. Furthermore, each dataset has salient visual landmarks (such as buildings) as well as aliasing visual landmarks, such as mountains covered by trees, grasslands and water areas. For each dataset, two remote aerial images taken at different times were obtained from the NearMap [66]; one was used to generate landmark reference images and the other one, which was taken at least 3 months later, was used to simulate camera images. Landmarks were defined as areas of 128 × 128 pixels evenly distributed with 32 pixels’ stride in the reference remote images. The diverse visual landmarks and visual appearance variations make the three datasets suitable for evaluating the proposed active navigation approach.

The Coast Dataset covers an area of 28 km × 18 km in Queensland, Australia, containing water areas, mountains covered with trees and buildings as shown in Fig. 5(a). Aerial image resolution in this dataset is 4.77 m per pixel, and the total number of landmarks is 19,936.

The Mountain Dataset is a small area of 2 km × 1.4 km in west Brisbane city, Australia, containing mountains and urban areas as shown in Fig. 5(b). The resolution of aerial images in this dataset is 0.55 m per pixel, and the database has 8658 historical landmark images.

The Village datasets is a 41 km × 28 km rural area in Queensland, containing mountains, grassland and farms, as shown in Fig. 7(c). The resolution of aerial images in this dataset is 4.77 m per pixel, and the total number of landmarks is 47,348.

#### 4.2 Experimental Procedure

To test the performance of the proposed navigation model, we conducted three groups of experiments, corresponding to the three system components – topological map creation, active path planning and path execution. Before the experiments, a training database was used to train the MAC feature embedding network, which was used to transfer the images into feature descriptors. The training dataset was captured at an area that is not included in any testing datasets and the training procedure followed our previous paper [55].
4.2.1 Topological Map Creation Experiments

The purpose of constructing a topological map is to partition the physical space into subregions at different reliability levels. Rightly estimate the landmarks’ reliability for landmark recognition is the basis for topological mapping. To verify the proposed reliability assessment method, we sorted the landmarks in reliability descending order and tested the landmark recognition precision at different reliability levels.

For each landmark reference image, a corresponding query image was generated by using the testing remote image. The query image has viewpoint, position and scale variations to the historical reference image, as shown as in Table 3, to simulate the real-world observation changes. In detail, the Coast query images have a viewpoint variation of 10° (anticlockwise), and the Village and Mountain query images have a viewpoint variation of 20° to the reference images. The observation position variation (represented in the remote map) along the east and south were set as a zero-mean Gaussian distribution. The Village and Mountain query images also have a zero mean scale variation, to simulate the observation height difference. Figure 6 demonstrates the variations between the query and reference images.

The landmark recognition approach described in Section 3.3 was used for performance evaluation. As the reliability assessment method is solely based on landmark appearance, only used Eq.(5) was used for landmark recognition in this group of experiments. The performance was characterized by landmark recognition precision, where a correct localization was defined as the recognized landmark is within 64σ meters to the query image’s true position, where σ is the corresponding remote image’s resolution. We also compared our reliability assessment method with an entropy-based reliability estimation method, which is expressed as:

\[ s_i = 1 - \frac{\sum_{k=1}^{256} p(f_i^k) \log_2 p(f_i^k)}{256} \]

Table 2  Path Execution Algorithm

|   | Path Execution Algorithm |
|---|-------------------------|
| 1 | **Input:** Initial position \( L_0 \)  |
|   | Database image features \( \{f_i\}_N \)  |
|   | Database image position label \( \{L_i\}_N \)  |
|   | Travel distance since the last position calibration \( L \)  |
|   | Path integration error ratio \( \rho \)  |
| 2 | **for all** odometry measurements \( dL_i \)  |
| 3 | Path integration as \( L_{Pl,t} = L_{Pl,t-1} + dL_i; L = L + ||dL_i|| \)  |
| 4 | **if** new camera image obtained  |
| 5 | Visual place recognition as in Eq.(5)  |
| 6 | \[ \text{if} \ \rho \cdot L \leq \|L_{rec} - L_{Pl,t}\|, \text{continue} \]  |
| 7 | \[ \text{else} \ L_{Pl,t} = L_{rec}; L = 0 \]  |
| 8 | **Output:** the estimated position \( L_{Pl} \)  |

Fig. 5 Remote aerial images showing the navigation environment of (a) the Coast (b) the Mountain and (c) the Village datasets
where $p(f_k)$ is a Gaussian distribution demonstrating the distribution of the k-th feature dimension of all the reference images, and 256 is the length of a MAC feature vector. The entropy-based reliability estimation method was used in previous work to weight bag-of-word visual features in place recognition [67].

Based on the reliability scores, we set three different thresholds while building the topological nodes; the percentage of landmarks above each threshold was 30%, 60% and 100% respectively. We also constructed different topological connections by adopting compasses at different accuracy levels. In detail, five different topological connections were built to demonstrate the reachability under 0°, 2, 5, 7 and 10 degrees’ compass errors.

### 4.2.2 Path Planning Experiments

In the second group of experiments, we tested the proposed active path planning method on 20 navigation tasks in each dataset. These navigation tasks were generated by sampling starting nodes and destination nodes in the topological map. In detail, the starting nodes were randomly sampled, and then the destination nodes were sampled to ensure the centres of the two nodes has a distance longer than half of the diagonal line of the remote aerial image. The proposed path planning method is closely related to the map topology. Therefore, we conducted the experiments under the five different topologies, which were constructed under different compass accuracy as described in Section 4.2.1.

| Dataset            | Viewpoint Difference | Position Difference       | Scale Difference |
|--------------------|----------------------|---------------------------|-----------------|
| Coast              | 10°                  | $x \sim \mathcal{N}(0, 5\text{pix})$, $y \sim \mathcal{N}(0, 5\text{pix})$ | –               |
| Village, Mountain  | 20°                  | $x \sim \mathcal{N}(0, 10\text{pix})$, $y \sim \mathcal{N}(0, 10\text{pix})$ | $s \sim \mathcal{N}(0, 0.1)$ |

Two passive path planning methods were also applied to make comparisons with the proposed active method. The first method is the shortest path planning method, which is a widely deployed robotic navigation strategy; this method puts aside the topological map and generates the optimal path in terms of path length. While the first passive method finds the shortest path in the physical space, the second method searches the path with the minimal number of nodes in the topological space; this path planning method has also been deployed in topological navigation systems [21, 59]. Both the two comparison methods have no considerations in the landmark recognition uncertainty along the planned path, while the proposed method actively include the future landmark recognition uncertainty in path planning.

### 4.2.3 Path Execution Experiments

In the third group of experiments, we simulated a virtual aerial robot, which was equipped with a downward-looking camera and a compass aided path integration component, to execute the 20 navigation tasks along the paths planned by the three methods as described in Section 4.2.2. The navigation uncertainty was characterized by the localization error.

The onboard virtual camera was defined to have a view filed of 90° and the output image was at the size of 128 × 128 pixels, with the optical axis at the middle of the image; the camera was set to take images at a frequency of 1 Hz. To reduce the viewpoint variation between the camera images...
and reference images, the virtual compass was used to rotate the camera to align with the remote aerial image’s direction.

The agent was set to fly along the planned path at a height of 64σ meters above the ground and at a speed of 20σ m/s along the heading direction, where σ is the remote aerial image resolution. Based on the agent’s ground truth position, the simulated compass orientation and the camera parameter, the corresponding image patch was extracted from the testing remote image to simulate the perceived camera image. The simulated camera images have viewpoint, translation differences as well as appearance variations to their nearby landmark reference images.

Moreover, noises to the visual path integration and compass were added to simulate the real-world navigation uncertainty. In detail, the measured compass orientation had a fixed 8 degrees’ orientation error to the truth orientation. The translation movements noise measured by path integration was set as a Gaussian noise which has zero mean and a standard deviation as 0.05dLt, where dLt is the measured translation movements during the t-th time interval. The details of the simulation parameters in the path execution experiments are shown in Tables 4 and 5.

5 Results

The results are presented in three parts corresponding to the three groups of experiments in section 4. The first part shows the effectiveness of the proposed landmark reliability estimation method and presents some examples of the constructed topological nodes. The second part demonstrates the path efficiency of the proposed paths and compares to the paths generated by the two conventional path planning methods, shown in Table 4. Finally, the localization uncertainty of the proposed active navigation approach and the two other methods described in section 4.2.2 are presented.

5.1 Landmark Reliability Estimation and Topological Map Creation

Figure 7 shows the landmark recognition precision at different reliability levels. The X-axis demonstrates the percentage of landmarks selected in reliability descending order and the Y-axis demonstrates the rightly recognized landmarks among the selected ones. As shown in Fig. 7, both for the proposed reliability assessment method (the L2 curve) and the entropy-based reliability method, the landmark recognition precision decreases as the reliability decreases; this demonstrates both methods are effective to assess landmark recognition reliability. Taking the Coast dataset for example, when selecting 60% of the landmarks in descending L2 reliability order, about 90% of them are rightly recognized; while only 63% of all landmarks are correctly recognized in the whole dataset.

Figure 8 shows some rightly recognized landmark examples, which are ranking at the top 10% in the descending order
reliability list. The reliable landmarks have consistent salient features in both the reference images and the query images, such as curving roads and buildings, which makes them easy to recognize. Figure 9 shows some falsely recognized landmark examples at the top 10%. Though there are salient features in the reference image, they failed to be recognized due to appearance, observation position and scale variations in the query images.

Based on the reliability score, we constructed the topological nodes at three different reliability levels as described in section 4.2.1. Figure 10 shows the nodes at the highest reliability level. In the Coast dataset, the most reliable nodes are mostly distributed at the boundaries of mountains/water areas and the towns; in the Village dataset, the reliable nodes are at the boundaries of trees/grass and the buildings; In the Village dataset, the reliable nodes are mostly distributed at areas that have buildings or curving road segments. The water regions in the Coast dataset, the similar street blocks in the Mountain dataset and the farmland in the Village dataset are deemed to have lower reliability.

5.2 Path Planning

This section presents the path planning results for the 20 navigation trials in each dataset by using the three methods presented in Table 4. Firstly, we compare the average number of nodes along the paths generated by the two topological path planning methods. Both methods use the same topological graphs in path planning, but the generated paths are quite different. Figure 11 shows, for both methods, the number of nodes building up the paths increases as the compass accuracy decreases. When the compass is perfect, the generated paths
only consist of two nodes: the starting node and the destination node. While the compass error gets larger, the edges connecting the nodes get fewer, thus more nodes are required to link up the starting node and the destination node. Meanwhile, within the same graph, the proposed active method utilizes more nodes to construct a path than the conventional passive method. This is mainly because the active method takes additional considerations in node reliability, resulting in some detours for retrieving reliable nodes.

Though retrieving more nodes in the topological space not strictly lead to longer travel distance in the physical paths, the average path length shows an increasing tendency as the compass accuracy gets lower, as shown in Fig. 12. While the shortest paths are always the most efficient, the proposed active method show less efficient than the conventional passive method.

Figure 13 shows some examples of the planned paths in the three testing datasets by using the same topological nodes with the topological connections constructed under 0, 5 and 10 degrees’ orientation constraints. The shortest paths are the same as the paths generated under perfect compass, therefore the figure only shows the example paths generated by the two topological path planning methods. As shown in the figure, the conventional topological path planning method takes no considerations in landmark recognition reliability, thus the generated paths pass across large areas of visually aliased landmarks, such as the water areas in Fig. 13(b), the mountain areas in Fig. 13(d) and (f). However, the active path planning method actively avoids travelling across the visually aliased areas and retrieves salient visual landmarks for navigation, most of which are at the boundaries of salient underlying landscapes.
This section shows the localization uncertainty when executing the paths generated by the proposed active navigation method. The used topological connections were built under 10 degrees’ compass error. To highlight the advantage of the proposed method, comparisons with the shortest paths and the conventional passive topological paths are also presented.

Table 6 shows the path execution results in the Coast dataset, where the navigation performance is characterized as the localization mean average error (MAE). Through the compass can constrain the orientation drift, the path integration (PI) has large localization errors in all the three kinds of paths. This is mainly because the measured motion error accumulates in the time integration process. Combining landmark recognition with the compass aided PI component, as proposed in section 3.3, can greatly reduce the localization error. However, the landmark recognition component reduces more localization drifts on the proposed active paths than on the shortest and the conventional topological paths. As shown in Table 6, the MAE of the proposed path execution method along the planned active paths is 189 m (about 50 pixels in the remote aerial image), which is only about 12% of the compass aided PI’s MAE along the same paths; meanwhile, the combined path execution method’s MAE along the shortest and the conventional topological paths are only 40% and 42% of the PI component respectively. The results demonstrate that

![Fig. 10](image1.png) The nodes at the highest reliability level in the (a) Coast, (b) Mountain and (c) Village topological map

![Fig. 11](image2.png) The average number of retrieved nodes along the planned paths under different graph topology

![Fig. 12](image3.png) The average path length under different graph topology
navigating along the proposed path achieves lower uncertainty than navigation on the shortest paths and the conventional topological paths.

Figure 14 shows an example of executing the shortest path and the proposed active path respectively. The green line demonstrates the estimated trajectory from the compass aided PI.
component, the red line demonstrates the proposed path execution method’s estimated trajectory, and the white line segments illustrate the proposed execution method’s localization error. As shown in the figure, most landmarks along the shortest path were unrecognized due to their aliasing appearance, such as the water areas; thus the path integration error accumulates and leading to the large localization errors as shown in Table 6. In contrast, the proposed topological navigation method prefers to use reliable nodes to construct the paths and avoids passing through the large aliased zones. Benefit from the proposed active navigation strategy, the agent can recognize most of the landmarks along the path to reduce the path integration drifts and achieve significant smaller localization errors.

Table 7 shows the localization errors in the Mountain dataset and Fig. 15 shows a path execution example. Same as the Coast dataset, the proposed PI and landmark recognition combined path execution method achieves smaller MAE than the PI only path execution method. Meanwhile, the combined execution method has the smallest MAE along the proposed active paths. This once again demonstrates the advantage of using the proposed active navigation method. The example shown in Fig. 15 presents that the proposed active navigation method avoids travelling across the mountain area, and utilize salient landmarks along the mountain/city boundaries to reduce navigation uncertainty; this navigation behaviour is similar to the observed pigeon’s homing strategy [7, 8].

Table 8 shows the localization errors in the Village dataset. The compass aided PI component’s MAE are larger than 2000 m on all the three kinds of paths. Incorporating with landmark recognition can reduce the MAE greatly. For example, the localization MAE of the combined path execution method on the shortest and the conventional topological paths are only 718.0 and 800.7 m, which are 35% and 36% of the PI’s MAE respectively. Note that, combing landmark recognition achieves the most notable result on the proposed active paths, where the MAE of the combined path execution method is only 11% of the PI’s MAE. Moreover, the combined path execution method also achieves the smallest MAE when the agent navigating along the planned active paths.

As shown by the example in Fig. 16, for the shortest path, the landmarks on the mountain area are unrecognized due to its aliased appearance; this lead to the accumulation of path integration drifts. However, the proposed method can actively find a reliable path for landmark recognition, which in turn brings in higher localization accuracy.

6 Discussion and Future Work

This paper presented a topological navigation model for aerial mobile robots, which is inspired by the animal’s active navigation behaviours. The proposed approach addressed reducing the navigation uncertainty by actively visiting a sequence of reliably recognizable areas. The experiments in different
visual environments have demonstrated the effectiveness of the proposed approach. The experimental results have also suggested that there are tradeoffs between path reliability and path efficiency.

The proposed approach has presented novel components including topological map creation, active path planning and path execution for aerial mobile robotic applications. In the following, discussion and future work for each component of the proposed navigation model are presented.

6.1 Topological Map Creation

The topological map is the basis of the proposed navigation model; it partitions the physical space into node areas at different reliability levels such that the agent can actively retrieve the reliable node areas for safe navigation. While we provide a method to assess the landmark reliability and build circular nodes, future work could employ other reliability assessment methods and topological node constitution methods to create the topological map.

In the proposed approach, the landmark recognition reliability is modelled as the feature distance as in Eq. (1). Recently, some work has investigated assessing local features’ importance within an image to avoid aliasing features in place recognition [52–54]. [54] proposed a reweighting mask to assign different importance scores to different ConvNet patterns for visual place recognition. In the future, we can extend the reweighting technique to learn reliable areas among the global visual environment for node construction.

While experiments have shown that visual cues are important for animal’s active navigation behaviours, other non-visual stimuli, such as olfaction and somatosensation cues, also play a role in active navigation [11, 30]. The olfaction cues are also suggested to act as landmarks for homing pigeon and insects [10, 68]. Future work could combine multisensory information with a multi-sensory reliability assessment method to develop an active goal-directed navigation system [69].

6.2 Active Path Planning

Currently, how animal evaluates and plan their paths to distant goals is poorly understand; existing research has demonstrated that path planning behaviours recruit a complex neural circuit including the prefrontal cortex, thalamus and hippocampus [35, 70]. In the proposed method, we employed a topological map to mimics the topological spatial cognition and used a reward diffusion process to simulate the evaluation process in the brain.

When building topological connections, we considered the worst-case situation to guarantee that the agent starts at any location in the current node can hit their connected node, as

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Table 7 MAE error of different navigation methods in the Mountain dataset

| Execution Method          | Mean Average Localization Error (m) |
|---------------------------|-------------------------------------|
|                           | Shortest Path | Passive Path | Active Path (proposed) |
| Compass aided PI         | 103.6          | 105.7        | 101.7                   |
| Proposed Execution Method| 54.5           | 73.0         | **41.7**                |

---

Fig. 15 Path execution example from the Mountain dataset. (a) Executing the shortest path and (b) executing the proposed path.
shown in Fig. 3. Future work can relax the geometric constraints in edge construction to enrich the connectivity of the topological graph. Currently, the path planning process is performed offline; future work could develop an online path planning method so that the agent can adjust the path based on the current landmark recognition performance.

Recently, some researchers have used reinforcement learning techniques to learn grid-like spatial representations to mimics the grid cells in the brain. Based on the grid-like spatial representation, they also employed an end-to-end reinforcement learning method to learn navigation policies [71]. One potential interesting work would be incorporating our topological map in the end-to-end navigation policy learning such that the agent can have more flexible navigation choices.

6.3 Path Execution

Navigation is executed by using a compass-aided PI to generate orientation guidance and using a camera to perform visual landmark recognition. As the path integration component is not the key research point in this work, we used a virtual PI component, in which we also added noises, to estimate the agent’s motion states. Future work could use a filter-based [72] or an optimization-based [73] fusion method to integrate the compass, camera and other sensor data to perform real path integration.

The deployed landmark recognition method can determine whether the current camera image is taken at a known landmark or not; however, it cannot estimate the position variations related to the landmark position label. A future improvement method can use camera geometry to calculate a more precision position from the point correspondences between the camera image and the recognized landmark image, as exemplified by the loop closure component in a simultaneous localization and mapping system [73].

7 Conclusion

We have proposed a bio-inspired topological navigation model for aerial mobile robots to reduce the real-world navigation uncertainty. A novel topological mapping approach was developed to build nodes to represent spatial regions at different reliability levels, and to construct edges to demonstrate the reachability between the nodes. Then, a new active path planning method was introduced to search the topological graph to generate reliable paths to distant goals. The experimental results have shown that the proposed model generates animal-like navigation behaviours, which avoids travelling across large visually aliased areas, such as forest and water regions. Navigating on the proposed paths also achieves higher localization accuracy than navigating on the shortest paths and the conventional topological navigation paths, but at the cost of a

![Fig. 16 Path execution example from the Village dataset. (a) Executing the shortest path and (b) executing the proposed path](image-url)
longer travel distance. In a complementary way, this study enhances insights on how active navigation strategy can deal with real-world navigation uncertainty faced by both robots and animals.

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