Navigating Points of Interest: The Dog-Walker Pathfinding Algorithm

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Abstract: Navigating complex environments that encompass both road networks and points of interest (POIs) demands innovative pathfinding solutions. Traditional algorithms, such as Dijkstra's, primarily focus on finding the shortest path between nodes on a graph and are not designed to handle the additional complexity of scattered POIs. This paper introduces the dog-walker pathfinding algorithm, a novel approach that integrates the discovery of waypoints and greedy routing into a single process. By simulating the dynamics between two agents—a dog motivated by POIs and a walker navigating a graph—the algorithm dynamically identifies routes that connect key locations and pass through areas rich in POIs. This method leverages road networks and POIs to provide routes from the start point to the end point tailored to user preferences. Owing to the minimal data requirements for POIs, this method can be easily integrated with various data sources, including X(formerly Twitter), Google Maps, and Instagram. In this study, we develop an agent-based online algorithm inspired by the dogwalker. We verified the algorithm using POI data obtained from Flickr and Google Maps, demonstrating its application in real-world scenarios such as recommending tourist routes. Demonstrations show that our algorithm effectively generates routes that align with user preferences, as evidenced by qualitative and quantitative assessments. Additionally, we demonstrated that our method operates more rapidly than methods utilizing Dijkstra's algorithm.

1 INTRODUCTION

Pathfinding algorithms are essential for numerous applications related to real-world mobility. They are widely used for finding the shortest route between two points in large graph data, such as road maps. Additionally, these algorithms help manage complex queries such as route optimization, automated driving, and tourist route recommendations.

In this paper, we introduce the dog-walker algorithm, a novel method designed to find routes that cater to user interests within large graph data spaces with numerous point of interest(POIs).

The proposed method utilizes data from Open Street Map[1] and Flickr[2] . Figure 1 illustrates the targeted spatial area. By integrating geographical information and social media content, this approach enriches the analysis and enhances the precision of the methodological application. In our graph, road network edges are depicted by blue lines, while POIs are represented by red dots. The algorithm identifies efficient routes in such spaces, favoring regions with a high density of POIs.

Traditionally, algorithms such as Dijkstra's are used to find optimal routes on graphs. However, these methods are not equipped to handle spaces where both graphs and POIs coexist, as targeted in this study. In typical road networks, nodes are placed at intersections, but our usual start and end points, such as buildings or parking lots, are not directly on the road. Similarly, most landmarks do not reside directly on the road.

This concept is particularly suited for applications using geosocial big data. For instance, consider the graph as a road network and the POIs as geotagged photos shared on social media sites. A geotag represents the latitude and longitude coordinates where the photo was taken, provided by the GPS of a smartphone or other device. Locations with a high density of geotags are noteworthy. Geotags often exist independently from the road network and may have a fuzzy density distribution due to GPS errors.

The objective of the proposed method is to discover routes on the road network that pass through

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[2] https://www.flickr.com

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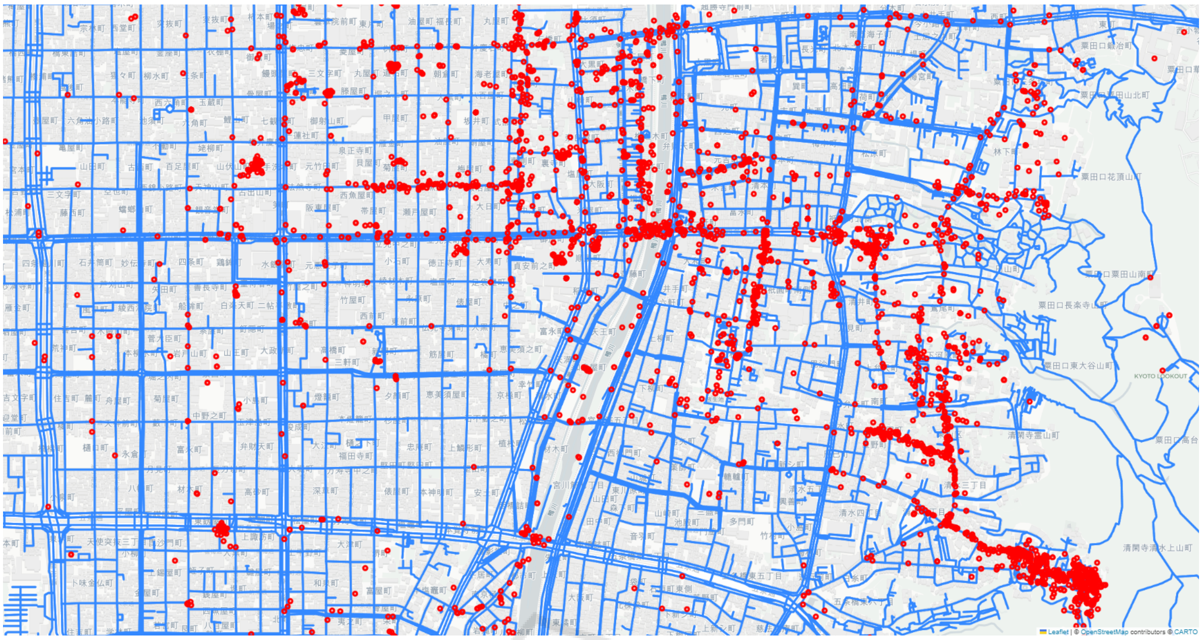


Figure 1: OpenStreetMap data in Kyoto Prefecture, Japan. Blue lines represent road network edges and red dots represent POIs.

locations with a high density of POIs that are not directly on the road network but exist in the same space.

This algorithm can be applied to recommend sightseeing routes based on geosocial data. Conventionally, recommending tourist routes required two steps: recommending waypoints and discovering routes connecting them. For example, POIs are density-clustered by DBSCAN, and routes are discovered using nodes in the cluster as waypoints. In contrast, the proposed method is an online algorithm that simultaneously discovers waypoints and optimal routes.

The dog-walker pathfinding algorithm works on the principle of two agents: a dog and a walker. The walker navigates the graph, while the dog moves independently within a two-dimensional space, motivated by POIs. The dog and walker are linked by a lead, with the walker propelled in the direction the dog wishes to go. The dog, motivated by POIs acting as food, moves toward areas where POIs are abundant. Once the dog has consumed enough POIs, it gravitates toward its goal. The path that the walker takes, led by the dog, is the output of this algorithm, anticipated to pass through areas with a high density of POIs.

The contributions of this study are as follows.

1. Identifying waypoints based on POIs.
2. Discovering efficient routes around waypoints.
3. Developing an algorithm that combines the above two steps.
4. Creating agent-based online algorithms inspired by the dog-walker concept.
5. Demonstrating a strong relevance to real-world applications.

In this study, we qualitatively and quantitatively evaluated the recommended routes assuming user preferences using geosocial data, and the results indicated that route recommendations were effectively made.Additionally, we demonstrated that our method operates more rapidly than methods utilizing Dijkstra's algorithm.

The remainder of this paper is structured as follows: Section 2 covers related work, Section 3 details our proposed method, Section 4 presents the experiments, and Section 5 concludes the paper and outlines future work.

2 RELATED WORK

Research utilizing geotagged social data has explored not only route recommendations based on user preferences but also methods that consider various factors such as time, distance, route safety, weather, and crowding as costs in the calculation. Additionally, studies have focused on identifying popular tourist spots using geotagged social data.

Yang et al. (Yang et al., 2011) proposed a versatile and highly accurate method for identifying tourist spots using geotagged social data collected from Flickr in Paris, Hong Kong, and New York. This method employs self-tuning spectral lustering, which does not require parameter settings, allowing for consistent clustering applicable to cities and locations with different POI characteristics.

Chen et al. (Chen et al., 2011) proposed a personal trajectory prediction system based on GPS data, using a new algorithm called Continuous Route Pattern Mining to extract route patterns. This system predicts future routes by utilizing route patterns extracted from an individual's past trajectory data. Popescu et al. (Popescu and Grefenstette, 2009) developed a method to estimate visit times and daily tourist routes using geotagged social data from Flickr in London, New York, Paris, and San Francisco. The proposed method automatically estimates visit times to tourist locations by utilizing the timestamps and location information of photos posted by users. Kurashima et al. (Kurashima et al., 2010) proposed a system that models the history of places visited by tourists using geotagged social data from Flickr in New York and San Francisco. This system recommends travel routes based on the user's current location and individual interests, leveraging data from large-scale photo-sharing sites for route recommendations, unlike previous studies that utilized GPS data. Ishizaki et al. (Ishizaki et al., 2021) introduced an algorithm called P-UCT that recommends routes best matching user preferences. The method includes generating evaluators using Support Vector Machine and route generation using Monte-Carlo Tree Search. Jie et al. (Bao et al., 2012) developed a system that automatically learns user preferences from location histories and extracts local expert opinions to provide recommendations. This system utilizes data collected from Foursquare in New York and Los Angeles. All of these route recommendation and estimation methods require user movement records and specific data sources, leading to challenges in data acquisition and the insufficiency of necessary data in certain regions.

De et al. (De Choudhury et al., 2010) proposed a method for generating tourist routes using geotagged social data from Flickr. This method uses geographic and temporal information to create timed paths based on each user's visited locations, stay durations, and travel times. By applying an orienteering problem algorithm (Tsiligirides, 1984), the system recommends optimal travel routes. Furthermore, Majid et al. (Majid et al., 2015) introduced a method for recommending suitable tourist destinations and travel routes using geotagged social data from Flickr, tourist data from Google Places, and historical weather data. These studies differ from our research in that they require pre-existing information about tourist spots for route recommendations. Jain et al. (Jain et al., 2010) proposed a system called Antourage to recommend tourist routes using geotagged social data from Flickr. In this method, users specify a starting point and a maximum travel distance, and the system suggests routes that visit popular tourist destinations within those constraints. The route exploration algorithm employs the Max-Min Ant System, a metaheuristic algorithm developed based on the behavior of real ants, as proposed by Dorigo et al. (Dorigo et al., 1996) (Dorigo and Gambardella, 1997) (Dorigo and Di Caro, 1999). It is primarily applied to combinatorial optimization problems and is particularly effective for the Traveling Salesman Problem (TSP). This algorithm consists of pheromone trails, pheromone updates, probabilistic path exploration, and an iterative process. Antourage recommends tours that visit popular tourist destinations; however, its optimization algorithm is time-consuming, making it unsuitable for online processing.

Kim et al. (Kim et al., 2014) proposed a navigation system called SocRoutes, which uses crime history data from Chicago and geotagged social data from X to suggest routes based on the regional context, particularly emotions. Unlike traditional navigation systems that suggest routes based on the shortest distance or fastest time, SocRoutes considers emotional context when suggesting routes. Fu et al. (Fu et al., 2014) introduced TREADS, a travel route recommendation system that leverages social media data, specifically X and Yelp reviews, to recommend safe and interesting travel routes in real time. TREADS takes into account the user's interests and safety, employing text summarization techniques to provide summaries of X data and Yelp reviews related to the locations on the recommended route. Quercia et al. (Quercia et al., 2014) developed a system that recommends not only the shortest route in urban areas but also emotionally pleasant routes. They retrieved the top k-shortest paths and evaluated these routes using geotagged data based on criteria such as "beautiful," "quiet," and "happy." These route exploration methods are designed for specific purposes, unlike our research, which aims to integrate multiple user preferences and interests.

Yamashita et al. (Yamashita and Yokoyama, 2022) proposed a method for recommending routes based on user preferences by dividing a map into a grid and assigning weights to the edges of the graph based on nighttime light data and geotagged tweets from X. They applied Dijkstra's algorithm to find optimal routes. While this method shares similarities with our research in terms of integrating various data sources and recommending routes based on user preferences, it relies on Dijkstra's algorithm (Dijkstra, 1958), which tends to avoid recommending routes that significantly deviate from the shortest path. In contrast, our study allows for adjusting the extent to which POIs are collected based on parameters, thus recommending more interesting detours.

3 PROPOSED METHOD

This section details the proposed method. Figure 2 provides an overview of our methodology, which is divided into three phases: dataset, preprocessing, and main processing.

The dataset phase consists of POI data (Section 3.1) and road network data (Section 3.2). During preprocessing, we extract specific POIs from the POI data (Section 3.3) and remove dead-end nodes from the road network (Section 3.4), overlaying them onto the same plane. We then assign POIs to each node (Section 3.5) and precompute the interest vectors (Section 3.6). In the main processing phase, we set start and end points on the preprocessed data, apply Dijkstra's algorithm (Section 3.7) to construct the shortest path tree, and execute the dog-walker pathfinding algorithm (Section 3.8).

Additionally, "POIs-on-map" refers to the situation where POIs overlap on the road network, while "Weighted POIs-on-map" indicates a state where data has been preprocessed, with POIs assigned to each node.

3.1 Data on POIs

We use geotagged POI data for route searching. The POI data requires only coordinate information on a two-dimensional plane (latitude and longitude), making it applicable to various data sources.

We utilize geotagged data shared on social networking services as POI data. Geotags represent the coordinates where the data were posted, suggesting that areas with high geotag density may contain points of interest. Therefore, our method suggests a route that includes waypoints densely populated with geotags en route to the destination. We have employed data from sources such as Flickr and Google Maps[3]; however, our methodology is adaptable to various sources, including Instagram [4] and X [5], allowing for the integration of different data sources.

[3]https://www.google.com/maps

[4]https://www.instagram.com

[5]https://www.x.com

3.2 Road Network

We define the road network as a simple undirected graph with non-negative weights, excluding one-way streets. The graph is denoted as $G = (V,E)$, where V represents the set of nodes, and E represents the edges of the road network. Each edge is represented as an unordered pair of vertices, $u, v \in V$, where $(u,v) \in E$ and $u \neq v$.

The cost between nodes is represented as $w(u,v)$, where $w(u,v) = w(v,u)$ and $w(u,v) > 0$. Each node has associated two-dimensional coordinate information; if the coordinates of nodes u and v are x_u and x_v, respectively, then $\boldsymbol{x_u} \neq \boldsymbol{x_v}$ when $u \neq v$.

Furthermore, we denote the straight-line distance between coordinates $\boldsymbol{x_u}$ and $\boldsymbol{x_v}$ as $l(\boldsymbol{x_u}, \boldsymbol{x_v})$. However, $l(\boldsymbol{x_u}, \boldsymbol{x_v})$ does not necessarily equal $w(u,v)$ because real-world roads are not composed of straight lines.

3.3 Extraction POIs

The extracted POIs contain various metadata depending on the dataset. For instance, Flickr provides metadata such as latitude and longitude, images, creation time, text, and tags. Google Maps might include reviews and store names. These metadata are used to extract subsets according to user preferences. For instance, data extracted from Flickr using the text "temple," can be used by tourists interested in visiting temples.

In this study, we focus on the dog-walker pathfinding algorithm and do not discuss the method of extracting data based on user preferences. However, our method assumes that the POIs, based on user preferences, only require latitude and longitude, making it compatible with various datasets.

3.4 Removal of Dead-End Nodes

The proposed method relies on the dog agent moving toward POIs, which makes it vulnerable at dead-end nodes. This occurs because the dog agent is drawn to the POIs regardless of dead ends, leading to a loop when a waypoint exists beyond the dead-end node. To ensure efficient navigation, a preprocessing step is necessary to remove these nodes. Therefore, we removed the dead-end nodes using the existing method by Jiyoung et al (Pung et al., 2022).

We remove edges connected to nodes of degree one, ensuring that each node v in the graph G satisfies $\deg(v) \geq 2$.

Additionally, road networks often represent the same street with two edges separated by lanes, such as in multilane roads. Thus, merely deleting nodes

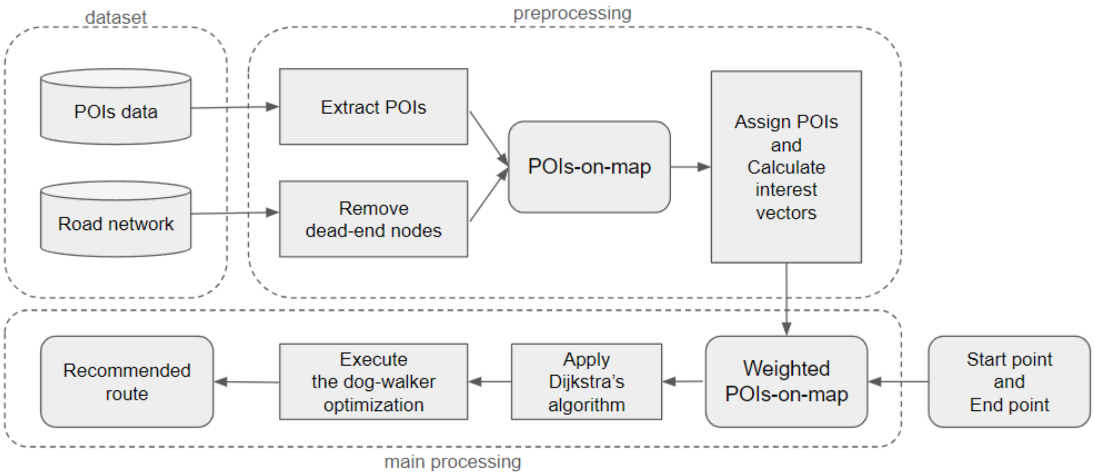


Figure 2: Overview of proposed method.

of degree one does not completely remove dead-end nodes. However, this issue is peripheral to our core problem and will not be further discussed here.

The preprocessed road network graph and the extracted POIs are combined on the same plane as POIs-on-map, which is then passed on to the subsequent processing.

3.5 Assigning POIs

For each node, we record a set of POIs within a distance $L[m]$ (in m). To calculate the distance between a node and a POI, we use the Haversine formula, which treats the Earth as a perfect sphere using spherical trigonometry. If the longitude and latitude of point A are (ϕ_a, ψ_a) and those of point B are (ϕ_b, ψ_b), the distance between points A and B is given by the following formula:

$$L = R\cos^{-1}(\sin\psi_a \sin\psi_b + \cos\psi_a \cos\psi_b \cos\Delta\phi) \tag{1}$$

As shown in Figure 3, when an agent reaches a node, the POIs recorded at that node are considered to be collected by the dog agent. The nodes that have been collected in this manner no longer influence subsequent route searching. This process is detailed further in Section 3.8, "Execution of the Dog-Walker Pathfinding Algorithm."

3.6 Calculation of Interest Vectors

For each node, the sum of the dog's interest vectors for all POIs is calculated using the following formula:

$$\mathrm{d}(\boldsymbol{x_i}, \boldsymbol{x_p}) = \frac{1}{|\boldsymbol{x_p} - \boldsymbol{x_i}|^n}(\boldsymbol{x_p} - \boldsymbol{x_i}) \tag{2}$$

$$\boldsymbol{I_i^D} = \sum_{p \in \mathbf{P}} \mathrm{d}(\boldsymbol{x_i}, \boldsymbol{x_p}) \tag{3}$$

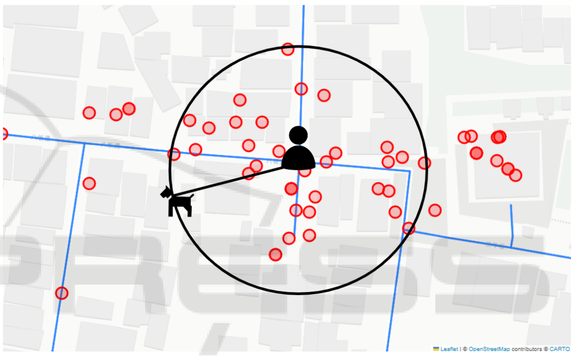


Figure 3: Collection method of POI by the dog agent in the proposed route recommendation system. The walker agent (depicted as a human silhouette) remains at the reached node, while the dog agent (depicted as a dog silhouette) collects POI (red circles) within a defined radius (black circle) around the node.

Description 1. *Blue lines represent road network edges and red points represent POI.*

Here, $\mathbf{P}$ represents the set of POIs, $\boldsymbol{x_p}$ is the position vector of a POI, $\boldsymbol{x_i}$ is the position vector of a node, and n is a parameter that determines the weight given to distance. A larger value of n indicates a greater interest in nearby POIs. The dog agent determines its next node based on this interest vector $\boldsymbol{I_i^D}$.

3.7 Application of Dijkstra's Algorithm

When a user specifies the start and end points in latitude and longitude, the nearest nodes are identified and assigned as the respective start and end points. Subsequently, Dijkstra's algorithm is applied starting from the end node to construct the shortest path tree, recording the parent of each node in the process. This information enables the walker agent to navigate toward the end node.

This process is initiated after the user provides the start and end points, thus constituting a part of the online processing phase. As such, Dijkstra's algorithm incurs a computational cost of $O(N \log M)$, where N represents the number of nodes and M the number of edges.

3.8 Execution of the Dog-Walker Pathfinding Algorithm

This section describes the dog-walker pathfinding algorithm. In the proposed method, the agent begins at the start node and follows these steps until it reaches the end node: (1) retrieve POIs, (2) recalculate the interest vector, and (3) determine the next node.

3.8.1 Retrieval of POIs

The dog agent collects POIs within a radius of $L[m]$ from the reached node and stores them in a set. Once collected, these POIs no longer influence any node. The targeted POIs are assigned to nodes during preprocessing, and except when L is excessively large, the overall computational complexity remains within approximately $O(|P|)$. ($|P|$ is the number of POIs)

As the collected POIs no longer have any influence, it is necessary to recalculate the interest level when deciding the next node. The method for recalculating this interest level is detailed in the following section.

3.8.2 Recalculate the Interest Vector

When the agent decides the next node, it calculates the interest vector I_i following the formula:

$$\boldsymbol{I_i} = C\boldsymbol{I_i^D} + \boldsymbol{I_i^W} \tag{4}$$

Here, $\boldsymbol{I_i^D}$ represents the dog's interest vector for POIs at the current node that have not yet been collected, while $\boldsymbol{I_i^W}$ represents the walker's interest vector. Therefore, the interest vector $\boldsymbol{I_i}$ for the agent is determined by the sum of the interest vectors of both the dog and the walker. Additionally, C is a parameter that dictates whether the dog or walker has a greater influence on decision-making.

As the movement of the node is determined by the direction of the vector $\boldsymbol{I_i}$, scalar values are essentially meaningless in this context. Therefore, the parameter is set for only one of the terms.

$$\boldsymbol{I_i^D} = \begin{cases} \sum_{p \in \mathbf{P}} \mathrm{d}(\boldsymbol{x_i}, \boldsymbol{x_p}) - \sum_{q \in \mathbf{Q}} \mathrm{d}(\boldsymbol{x_i}, \boldsymbol{x_q}) \\ \sum_{p \in \mathbf{P} \setminus \mathbf{Q}} \mathrm{d}(\boldsymbol{x_i}, \boldsymbol{x_p}) \end{cases} \tag{5}$$

Here, $\mathbf{Q}$ is the set of collected POIs. If the set of collected POIs is less than half of the total POIs, the calculation is done by subtracting from the preprocessed interest vectors. If more than half, the interest vectors of the uncollected POIs are added to find the dog's interest vector. This yields the same result with either formula, regardless of the number of collected POIs. However, for a large number of POIs, or when few POIs are collected, this can significantly reduce execution time.

Additionally, $\boldsymbol{I_i^W}$ is calculated according to the following formula:

$$\boldsymbol{I_i^W} = \frac{L_{now}}{L_{min}} \mathrm{d}(\boldsymbol{x_i}, \boldsymbol{x_j}) \tag{6}$$

Here, j denotes the parent node of i, and $\boldsymbol{x_j}$ and $\boldsymbol{x_i}$ represent the coordinates of these nodes, respectively. L_{min} is the shortest path length from the origin to the destination calculated a priori using Dijkstra's algorithm, while L_{now} denotes the cumulative distance traveled by the agent from the start node to its current node. Consequently, as the path length increases, the walker agent experiences a stronger compulsion toward the end node.

3.8.3 Determining the Next Node

The next node is determined by selecting the node that has the highest cosine similarity between the direction vector from the current node to an adjacent node and the interest vector.

$$k = \mathrm{argmax}_j \frac{\boldsymbol{I_i} \cdot \boldsymbol{v}i, j}{|\boldsymbol{I_i}||\boldsymbol{v}_{i,j}|} \quad (i, j \in \mathbf{E}) \tag{7}$$

Here, $\boldsymbol{v}_{i,j}$ represents the direction vector from node i to node j. If the next node is not the end node, the agent repeats this process starting from the POI collection phase.

Our method requires calculating the influence from each POI as the agent moves between nodes, which can be time-consuming for route search. The worst-case computational complexity of the route search is the product of the number of nodes traversed and the total number of POIs used. Therefore, the computational complexity increases proportionally with the number of POIs. However, as the POIs collected by the agent do not affect subsequent route searches, the number of POIs that influence the search decreases as the search progresses. Moreover, if the influence of all POIs and the set of nearby POIs is precomputed for each node during preprocessing, the actual execution time becomes significantly faster than the theoretical computational complexity.

4 EXPERIMENTS

In this section, we describe the datasets used, and present the results and analyses of the experiments.

4.1 Datasets

4.1.1 Flickr

Flickr is a photo-sharing platform that allows users to upload, share, and tag photographs and videos. It features an extensive database of billions of images, many of which are geotagged. This geotagged data have been utilized in a wide range of fields, including geographic information system (GIS) research, computer vision, and social sciences for analysis and visualization purposes.

However, our proposed method does not rely on user movement histories or images, which enhances its compatibility with data sources other than Flickr. In this study, Flickr was chosen because of the ease of data acquisition and the large scale of its data sources.

4.1.2 Google Maps

Google Maps is a Web-based mapping service that provides satellite imagery, street maps, panoramic street views (street views), real-time traffic conditions (Google Traffic), and route planning for walking, driving, cycling, and public transit. As a rich source of geographic data, Google Maps been extensively used in various fields, including urban planning, transportation, and tourism. Detailed and frequently updated data aid precise planning and analysis of spatial patterns.

In our research, Google Maps was selected as the second source of POIs data because of the ease of data acquisition and availability of additional information such as reviews.

4.1.3 Open Street Map

Open Street Map is a free user-generated database of map data that offers a comprehensive array of geographic information, including roads, buildings, and terrain, from around the world. This platform is an open-source project that allows map data to be freely used for both commercial and non-commercial purposes.

Open Street Map data are utilized in a variety of applications such as location-based services, navigation tools, urban planning, and transportation system research.

4.2 Experimental Setting

For our experiments, we used Flickr data spanning three years, from January 1, 2021 to January 1, 2024. Data for specific segments in Times Square, Manhattan, New York, USA, and Kyoto City, Kyoto Prefecture, Japan were gathered from Flickr, Google Maps, and OpenStreetMap. These datasets includes POIs and road network data.

From Flickr, we extracted posts within the targeted segments that included relevant keywords in their descriptions or tags. Data extraction from Google Maps was conducted manually, selecting appropriate content within the targeted segments. The acquired road network data consisted of walker pathways within the designated segments.

In each experiment, we collected POIs and road network data within specified geographical boundaries. For Times Square, the collection was within the latitude range of 40.745149 to 40.767065 and longitude range of -73.996706 to -73.970711. Similarly, in Kyoto, the data were gathered within latitude 34.99054 to 34.99940 and longitude 135.76802 to 135.78408.

The acquired road network data consisted of walker pathways within the designated segments.

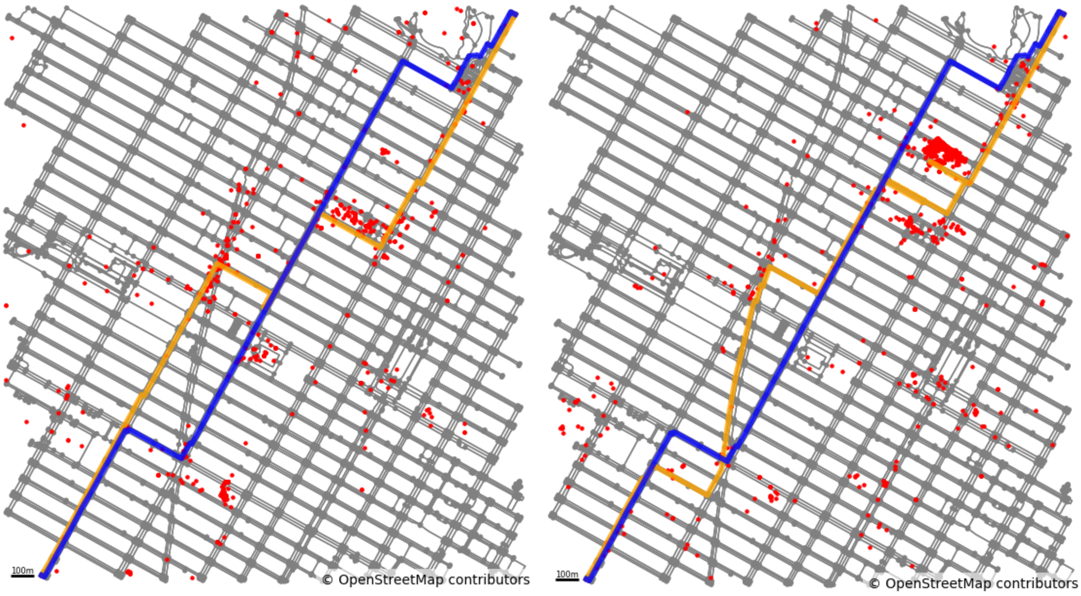
4.3 Experimental Result and Analysis

4.3.1 Experiments with Flickr Data

We conducted experiments using data from Flickr on Times Square, Manhattan, New York to validate our proposed method. Figure 4 (a) illustrates the results of a route search from latitude 40.74510, longitude -73.99670 to latitude 40.76710, longitude -73.97080, restricted to posts containing the text ‘cityscape.’ The blue route represents the shortest path, while the orange route depicts the path determined by our proposed method. Figure 4 (b) illustrates the results of a route search restricted to posts containing the text “art” in the same section.

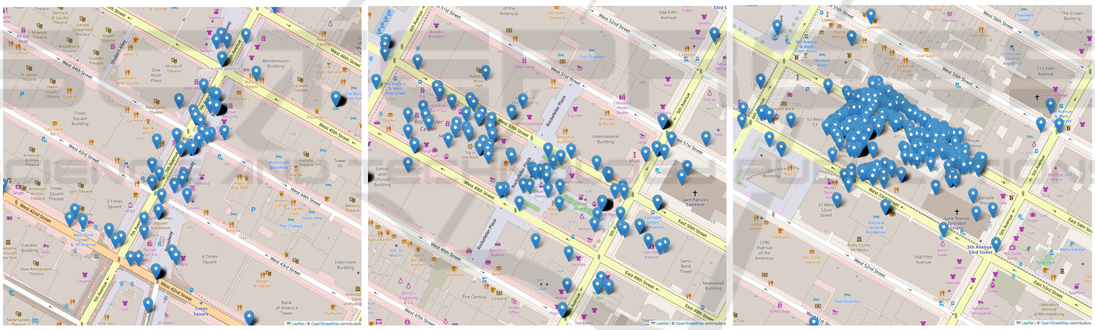
Figure 5 shows the waypoints traversed by the route determined by our proposed method, as illustrated in Figure 4. The first waypoint is along the 7th Avenue, a well-known and bustling area in Times Square. The next waypoint spans horizontally at the Top of the Rock observation deck, where most posts focus on the night view. Furthermore, for routes tagged with ’art’, after navigating several smaller waypoints, the route notably passes through a significant waypoint at The Museum of Modern Art (MoMA).

These figures demonstrate that the route generated by our proposed method effectively passes through



(a) cityscape (b) art

Figure 4: Results of the experiment that used the proposed method with Flickr data in parts of Manhattan, New York, USA. The gray, blue, and orange lines represent the road network, shortest route, and recommended route derived using the proposed method. Red dots represent POIs.



(a) 7th Avenue (b) Top of the Rock (c) MoMa

Figure 5: Details of waypoints passed by the proposed method in Times Square.

waypoints associated with the text ‘cityscape’ and ‘art’ within the area.

4.3.2 Experiments with Google Maps and Flickr Data

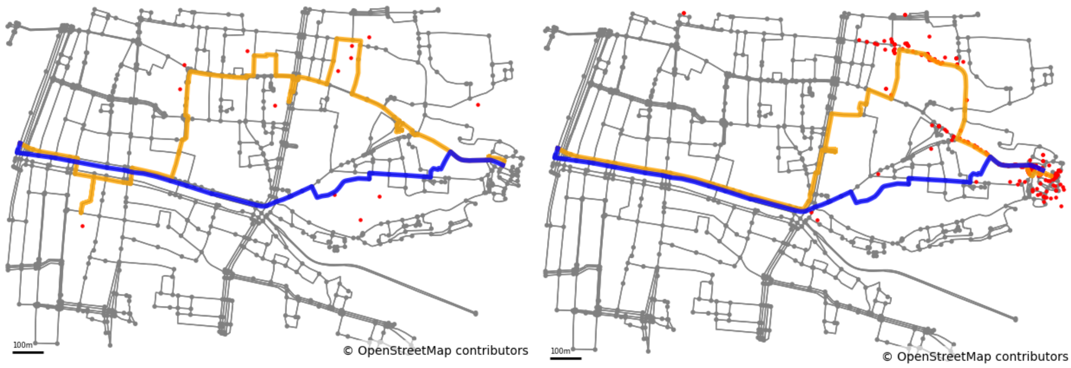
In Kyoto City, Kyoto Prefecture, we conducted experiments using data from Google Maps and Flickr to validate our proposed method. Figure 6 visualizes POIs related to ‘temple’ buildings along the popular tourist route from Kiyomizu-Gojo Station to Kiyomizu-dera Temple. In the experiments using Google Maps data, temples within the segment were designated as POIs, which are listed in Table 1.

Posts containing the keyword ‘temple’ within the studied segment were extracted from the Flickr data. In each figure, the blue and orange routes depict the shortest and recommended paths, respectively.

Figure 7 details the waypoints passed by the route recommended by our proposed method shown in Figure 6. The first encountered waypoint is the Yasaka Pagoda at Hokan-ji Temple, a renowned photographic landmark. The next waypoint is Kiyomizu-zaka, a major street leading to the Kiyomizu-dera Temple. These figures demonstrate that the route generated by our proposed method effectively passes through locations with POIs while heading toward the end node.

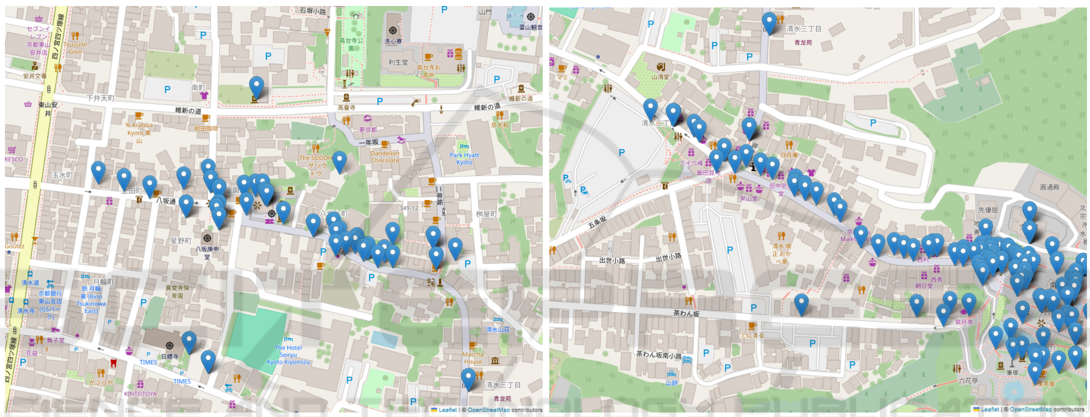
4.3.3 Experiments on Execution Time

We compared the execution times of the proposed method with those of a baseline method, utilizing the



(a) using Google Maps data (b) using Flickr data

Figure 6: Results of the experiment conducted using the proposed method with Google Maps and Flickr data in Kyoto City, Kyoto Prefecture, Japan. The gray, blue, and orange lines show the road network, shortest route, and recommended route derived using the proposed method. Red dots represent POIs related to 'temple.'.



(a) Hokan-ji Temple (b) kiyomizu-zaka

Figure 7: Details of waypoints passed by the proposed method in Kyoto.

Table 1: Coordinates of temples located in the target section.

temple name	latitude	longitude
Rokuharamitsu-ji	34.99722	135.77336
Rokudouchinnou-ji	34.99839	135.77537
Shoumyou-ji	34.99422	135.77081
Kiun-ji	34.99153	135.78051
Jippo-ji	34.99445	135.77829
Honju-ji	34.99464	135.77910
Saifuku-ji	34.99931	135.77395
Nittai-ji	35.02649	135.79178
Daizen-ji	34.99803	135.77891
Hofuku-ji	34.99634	135.77643
Hokan-ji	34.99872	135.77926
Kongo-ji	34.99851	135.77869
Tsumyoji	34.99405	135.77898
Kosho-ji	34.99698	135.78269
Juen-ji	34.99839	135.77116

road network of Times Square and artificially generated POIs. The baseline method employed two approaches: a simple execution of Dijkstra's algorithm between the start and end points, and an integrated approach combining DBSCAN clustering with Dijkstra's algorithm For this comparison, we measured only the execution time of the main processing after the user's start and end points had been provided.

In the proposed method, we generated a shortest path tree using Dijkstra's algorithm and subsequently executed the dog-walker pathfinding algorithm, measuring the duration required. For this analysis, we configured the proposed method with parameters that ensured all waypoints were visited, meeting the conditions of the baseline method. In Baseline Method 1, we calculated the execution time of Dijkstra's algorithm from the start point to the endpoint. In the baseline method 2, the route from the start to the end node was calculated multiple times using Dijkstra's algorithm to ensure all given waypoints were visited,

(a) Number of waypoints is 3 ($|POIs| = 30$)

(b) Number of waypoints is 4 ($|POIs| = 60$)

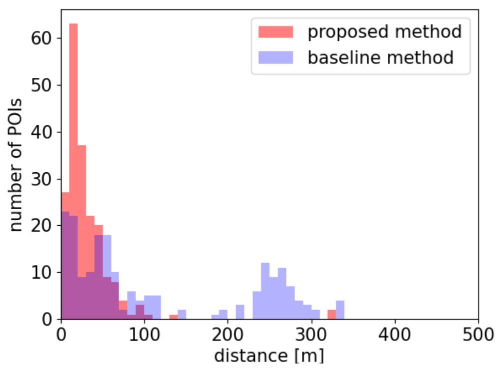
(c) Number of waypoints is 5 ($|POIs| = 90$)

(d) Number of waypoints is 6 ($|POIs| = 120$)

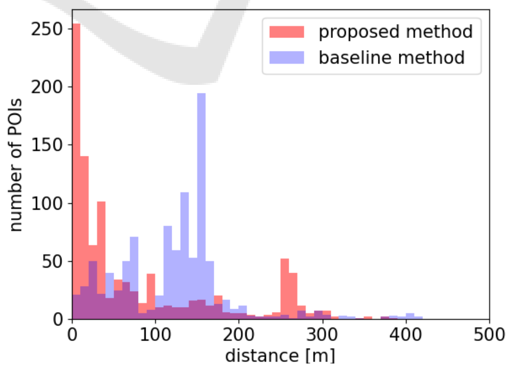
(e) Number of waypoints is 7 ($|POIs| = 150$)

(f) Number of waypoints is 8 ($|POIs| = 180$)

Figure 8: POIs-on-map using artificial data.



(a) Manhattan



(b) Kyoto

Figure 9: Distribution of the shortest distance between each POI and route.

and we compared the execution times. Here, the processing time for DBSCAN in the baseline method was not included in the computation time because it can be performed during preprocessing. Thus, the execution time for the baseline method is proportional to the time spent on Dijkstra's algorithm. Additionally, The waypoints generated for the experiment has 30 POIs each, randomly generated within a 50m radius from the center point to account for GPS errors.

Figure 8 illustrates the POIs-on-map when the

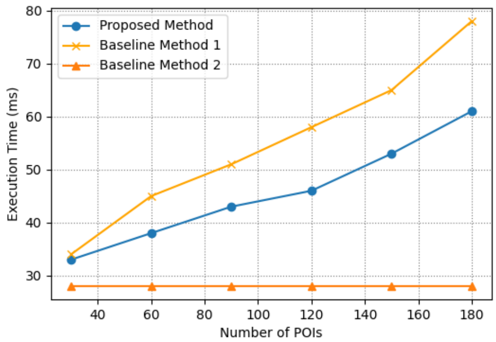


Figure 10: Execution time comparison among proposed and baseline method.

number of waypoints was varied from 3 to 8.

Figure 10 compares the execution times of the proposed method and the baseline methods. The experimental results indicate that, while the execution time of the proposed method is less efficient than the simple Dijkstra's algorithm, it outperforms when applied to routes involving waypoints.

In scenarios similar to those in Google Maps, where the number of POIs associated with each waypoint is low, the proposed method's execution time is notably shorter. Conversely, as the number of POIs belonging to each waypoint increases, the difference in execution time is expected to decrease.

In the baseline method 2, after deciding which size of waypoints to pass through using parameters, the order of movement must be manually configured. On the other hand, the proposed method excels as it integrates the discovery of waypoints and the determination of which waypoints to pass through within a single algorithm, allowing for automatic execution.

4.3.4 Experiments on Route Evaluation

We compared the distances between the proposed route and each point of interest (POI) with those generated by the baseline method. Figure 9 (a) presents a histogram of the distances between the route shown in Figure 4 (a) and each POI, while Figure 9 (b) corresponds to Figure 6 (b). These figures reveal that the POIs are more densely clustered around a 50-meter range in the routes generated by the proposed method compared to the baseline approach.

5 CONCLUSION & FUTURE WORK

In this study, we proposed a route recommendation method designed to effectively navigate through waypoints, conceptualized around the idea of dogwalker. The algorithm, named dog-walker pathfinding algorithm, operates based on the principles of two agents: a dog and a walker. The walker, serving as a navigating agent within the graph, moves independently in a two-dimensional space, separate from the dog. However, connected by a leash, the walker is propelled toward the direction the dog wishes to explore. Motivated by POIs acting as incentives, the dog tends to move toward areas abundant in POIs. Once the POIs are sufficiently consumed, the dog moves toward the goal, pulling the walker along a path that is expected to pass through high-density POI areas. This path is the output of our algorithm.

Experiments were conducted in two distinct areas: Kyoto City in Kyoto Prefecture, Japan, and Manhattan, New York, USA. As a result, it has been demonstrated that our method can recommend routes that effectively pass through POIs and operates faster than the baseline method using Dijkstra's algorithm. Future work will focus on further evaluation and refinement of this method. Generally, evaluating algorithms that use social big data is challenging. In this paper, we conducted a qualitative evaluation using Flickr and Google Maps as test datasets. For quantitative evaluation, there are several ideas, such as scoring based on the number of POIs passed or assigning scores based on reviews from Google Maps for specific buildings such as temples. However, these evaluations may vary depending on the context and could be influenced by parameters, potentially making them less reliable.

Various possibilities are available for refining our method, including optimizing parameter settings and the decision-making processes of the agents. Our method focuses on proposing an algorithm that effectively passes through waypoints in cases where POIs and the graph exist on the same plane but do not overlap; however, evaluation and algorithmic improvement are important, and hence will be prioritized in future work. Additionally, there is room for improvement in peripheral issues such as preprocessing the road network used and refining the data extraction methods.

REFERENCES

Bao, J., Zheng, Y., and Mokbel, M. (2012). Location-based and preference-aware recommendation using sparse geo-social networking data. pages 199–208.

Chen, L., Lv, M., Ye, Q., Chen, G., and Woodward, J. (2011). A personal route prediction system based on trajectory data mining. *Information Sciences*, 181(7):1264–1284.

De Choudhury, M., Feldman, M., Amer-Yahia, S., Golbandi, N., Lempel, R., and Yu, C. (2010). Automatic construction of travel itineraries using social breadcrumbs. In *Proceedings of the 21st ACM Conference on Hypertext and Hypermedia*, pages 35–44.

Dijkstra, E. (1958). A note on two problems in connexion with graphs. *Numb. Math.*, 1.

Dorigo, M. and Di Caro, G. (1999). Ant colony optimization: a new meta-heuristic. In *Proceedings of the 1999 congress on evolutionary computation-CEC99 (Cat. No. 99TH8406)*, volume 2, pages 1470–1477. IEEE.

Dorigo, M. and Gambardella, L. M. (1997). Ant colony system: a cooperative learning approach to the traveling salesman problem. *IEEE Transactions on evolutionary computation*, 1(1):53–66.

Dorigo, M., Maniezzo, V., and Colorni, A. (1996). Ant system: optimization by a colony of cooperating agents. *IEEE transactions on systems, man, and cybernetics, part b (cybernetics)*, 26(1):29–41.

Fu, K., Lu, Y.-C., and Lu, C.-T. (2014). Treads: A safe route recommender using social media mining and text summarization. In *Proceedings of the 22nd ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pages 557–560.

Ishizaki, Y., Koyama, Y., Takayama, T., and Togawa, N. (2021). A route recommendation method considering individual user's preferences by monte-carlo tree search and its evaluations. *Journal of information processing*, 29:81–92.

Jain, S., Seufert, S., and Bedathur, S. (2010). Antourage: mining distance-constrained trips from flickr. In *Proceedings of the 19th international conference on World wide web*, pages 1121–1122.

Kim, J., Cha, M., and Sandholm, T. (2014). Socroutes: safe routes based on tweet sentiments. In *Proceedings of the 23rd International Conference on World Wide Web*, pages 179–182.

Kurashima, T., Iwata, T., Irie, G., and Fujimura, K. (2010). Travel route recommendation using geotags in photo sharing sites. In *Proceedings of the 19th ACM international conference on Information and knowledge management*, pages 579–588.

Majid, A., Chen, L., Mirza, H. T., Hussain, I., and Chen, G. (2015). A system for mining interesting tourist locations and travel sequences from public geo-tagged photos. *Data & Knowledge Engineering*, 95:66–86.

Popescu, A. and Grefenstette, G. (2009). Deducing trip related information from flickr. In *Proceedings of the 18th international conference on World Wide Web*, pages 1183–1184.

Pung, J., D'Souza, R. M., Ghosal, D., and Zhang, M. (2022). A road network simplification algorithm that preserves topological properties. *Applied Network Science*, 7(79).

Quercia, D., Schifanella, R., and Aiello, L. M. (2014). The shortest path to happiness: Recommending beautiful, quiet, and happy routes in the city. In *Proceedings of the 25th ACM conference on Hypertext and social media*, pages 116–125.

Tsiligirides, T. (1984). Heuristic methods applied to orienteering. *Journal of the Operational Research Society*, 35:797–809.

Yamashita, O. and Yokoyama, S. (2022). Preference aware route recommendation using one billion geotagged tweets. In *Proceedings of the 6th ACM SIGSPATIAL International Workshop on Location-based Recommendations, Geosocial Networks and Geoadvertising*, pages 1–10.

Yang, Y., Gong, Z., and U, L. H. (2011). Identifying points of interest by self-tuning clustering. In *Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval*, pages 883–892.