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Route Recommendation System by Extracting Popular and Visible Landmarks

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Abstract: In this paper, we define three types of landmarks according to their properties, "point landmarks", "linear landmarks", and "area landmarks," those are not only visually distinguishable, but also easily noticeable based on human perception. Such landmarks are efficiently retrieved by analyzing microblogs. By exploiting the unique feature of those three types of landmarks, our navigation system can generate route directions, which is easy to remember and helpful for users to self-localize their position without heavily depending on their smart phones. In the experiment, we tested the system with virtual environment and confirmed that users of our system could reach the destination using a small number of landmarks, which means users need to check screens less than other system.

Keywords: Popularity, visibility, route recommendation, microblog, check-in, location-based SNS

1. Introduction

Although various route navigation systems have been developed so far, majority of the existing systems tend to provide efficient routes in terms of distance or time required to reach destinations. However, in reality, the route instructions given by automatic systems and those by humans tend to be different: *e.g.*, the former usually output instructions with street names used as reorientations, while the latter often use landmarks rather than street names [1]. Due to this mismatch, when following route directions suggested by automatic systems, users have to check the directions multiple times, resulting in eyeballing maps on small screens of their handheld devices. This not only makes the orienteering and way-finding difficult, but it also leads to concerns of safety while walking or cycling. Further, the systems cannot be used in case when GPS and/or digital map information are not available (*e.g.*, when travelling abroad). As a solution, a small number of instructions, especially by using landmarks, required for navigation is preferred, as being easy to be memorized and requiring low count of map

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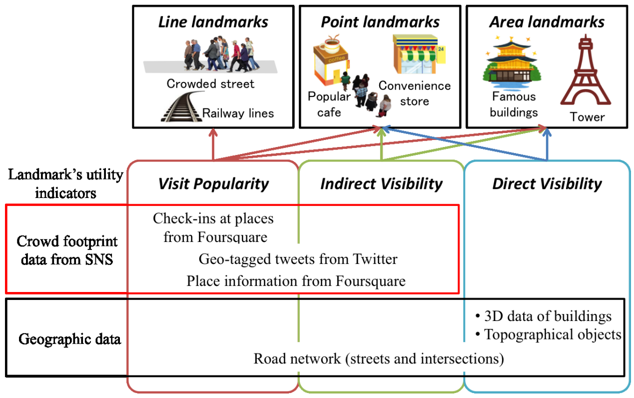


Fig. 1: Overview of useful landmarks.

references [2], [4], [6].

It should be noted that using landmarks is not only effective to instruct the route direction, but also helpful for users to self-localize their position; this is realized because landmarks increase users' spatial awareness by informing them about surroundings and decreasing effort required for constructing the mental representation of unfamiliar cities.

In the previous work, we propose an automatic system to efficiently generate memorable route using a small number of landmarks [6]. This is realized by introducing the three types of landmarks as shown in Fig. 1. Although the landmarks are only extracted based on visibility in the previous work, we further introduce human perception to extract the landmarks in the paper as follows:

Point landmark (Local landmark) is characterized by rather poor visibility, their relatively high visit popularity within local areas facilitates their discovery (*e.g.*, post office, restaurant, or library). Navigating users are expected to identify their locations accurately when having received a route recommendation with point landmarks. (*e.g.*, "Go straight and turn right at *the post office*.")

Line landmark is a continuous line connecting multiple intersections such as main streets, highways, rivers, and railways. **In the work, we further consider crowded streets as line landmarks.** Note that since line landmarks are characterized by 1D ambiguity along a route, they were not commonly used as landmarks.

Area landmark (Global landmark) A tall and distinctive structure can be recognized from far away. **In addition, we regard an area landmark to be gathering considerable crowd's attention even from users who are at different locations and cannot directly see the landmarks. Such places are characterized by their relatively high visit popularity and high indirect visibility as well.** "Walk toward *the red tower*." is an example of a route recommendation with an area landmark with previous technique and **"toward the center of downtown" is an example of new one.**

Based on the extracted landmarks we construct a route graph which facilitates optimal route search in terms of the number of landmarks as well as distance. We demonstrate an online route recommendation system [3] for San Francisco, Kagoshima and Kyoto cities.

2. Extracting Useful Landmarks

2.1 Measuring Visit Popularity of Places

First, popular places are extracted by measuring *visit popularity* for each place. Although there are several places characterized by many *checkins*, some of the checkins are repeatedly made by the same users (*e.g.*, owners of these places). We assume that the higher the number of unique users checked in at a place (*users*) is, the more popular the place is. Thus, we use then the number of users, *users*, checked in each place as the *visit popularity* of the place. Popular places whose *visit popularity* is over the value of a fixed threshold, these places are extracted as candidates of point and area landmarks. The way to compute their visibilities (direct/indirect) will be explained in the following sections.

2.2 Measuring Indirect Visibility of Places

Next, we compute *indirect visibility* for detected popular places. Famous places can be regarded useful landmarks and are often used for route navigation in the real world. Our approach relies on comparing the locations of users who mentioned a place in their tweets with the locations of places. This would indicate actually popular places that people talk about even without visiting them or before/after visiting them. The intuition behind this choice is that such places should have several clues enabling users to find the way to reach them, even if the users cannot directly see them. For instance, 'Kinkaku-ji Temple (Golden pavilion)' in Kyoto city, Japan cannot be seen from distant, but one can find various road signs at intersections that show directions to it, several buses bound for it and many related advertisements. As other examples, signs and advertisements of a shop will be explicit clues and people having a shop's original shopping bag can be regarded as an implicit clue.

Based on this reasoning, we define indirect visibility as the second indicator of the landmark's utility. In fact, this indicator is related to the concept of *collective spatial attention* [5] defined as the geographic area of interest and focus of multiple users. In this paper, our assumption is that popular places are typically mentioned by users who are nearby there. On the other hand, truly popular places are also referred by users at other distant locations.

We calculate *location difference* as the Euclidean distance between the coordinates of place of a tweet and the coordinates of intersection of the tweet. If the average value of *location differences* for a place is high, we can regard the place is indirectly recognizable from distant intersections.

2.3 Measuring Direct Visibility of Places

The third indicator for determining landmark's utility, *direct visibility*, is measured by analyzing 3D geographic data. In particular, high-rise buildings and towers which are seen from within larger areas can be detected based on this measure.

We use a map involving 3D shape information of all buildings in a city with 3D computer graphics (3DCG). Popular places are assigned to buildings based on their coordinates. In addition, top n tallest buildings are selected from all buildings in each block, which is set by dividing a target city into blocks, each of m km^2 size. Thus, we measure direct visibility of a place.

2.4 Classifying Places into Point and Area Landmarks

We describe here how to assign a landmark type based on the values of the three computed indicators. Note that extraction of line landmarks is explained in the next section. As for the places which have been found only by 3DCG methods, 0 is assigned as the values of their *visit popularity* and *indirect visibility*.

We determine "Area landmark" if the values of either indirect visibility or direct visibility of a place are high. The places characterized only by high visit popularity are regarded as point landmarks.

2.5 Extracting Line Landmarks

We detect crowded streets and consider them as line landmarks by measuring *visit popularity* of streets using the analyzed tweets. We first extract the set of crowded intersections which are determined based on the number of tweets assigned to these intersections. Next, we search for the set of sequential crowded intersections corresponding to segments of the same street. Each street is weighted by the total number of tweets sent from its respective crowded intersections. The value of weight of each street is then considered as *visit popularity* of the street.

3. Experiments

We developed an online prototype system [3] for landmark-based route recommendation for San Francisco, Kagoshima and Kyoto cities (Fig. 2). The system is evaluated in a virtual space by simulating the real world using Google Street View (SV) whose validity is also tested.

3.1 Datasets

We introduce datasets of SF city. 0.6M (millions) tweets are extracted. Then, the prototype system filters out tweets of users who had emitted $5,000$ and more tweets during the periods. Consequently, 0.57M tweets are utilized as the tweets dataset. We have constructed a database of places in SF city by gathering 25K places' basic attributes and crowd-sourced statistics from Foursquare which are a snapshot data. In terms of geographic information, fortunately, various datasets concerning SF city are provided in SF OpenData.

3.2 Extracted Landmarks and Recommended Routes

$2,604$ popular places were detected and 15 places with high indirect visibility were extracted. Based on this, 10 places were classified as area landmarks. Furthermore, in order to detect area landmarks by 3DCG based method, we selected the top 10 tallest buildings in each block. In total, 549 area landmarks were extracted based on their visibility from each intersection. Then the system detected 45 streets. By using these landmarks the system constructed a route graph and searched for a shorter route consisting of fewer landmarks. More details of the route graph construction and route search processes are provided in [6].

3.3 Evaluation

3.3.1 Settings

In order to evaluate routes we compare our proposed system with an existing route search system: Google Directions (GR). Furthermore, in order to confirm the usefulness of using crowd footprint data, we search for two types of routes by the proposed system. One (LR) uses landmarks extracted by considering both indirect visibility and direct visibility measured using both tweets and geographic data, and the other (VR) uses landmarks extracted by considering direct visibility measured using geographic data only.

In this study, 36 participants (28 males and 8 females) who have never been to San Francisco participated. They first received a route recommendation from a starting point to a destination and tried to remember it within 2 min. Then relying on their memory, they attempted to reach the destination in a simulated real space by operating SV[*1]. The materials about the recommended routes which were shown to the users included textual route directions from a starting point to a destination and a route path displayed on a map as well as images of landmarks, if any were included in the routes (see Fig. 3). During the experiments, these materials and a small screen enabling a participant to check his/her current location on a map (which is typically shown in the corner of the SV interface) were hidden from users unless the subjects asked to see them.

In order to evaluate recommended routes, we set three evaluation items as follows:

i) time (min.): How long did it take to reach a destination from a starting point?

ii) route ref.: How many times did you check route directions on a printed material about the route?

iii) self-position ref.: How many times did you check your self-position with Google Maps?

We recorded i) the time spent from a starting point to a destination, ii) a route directions' reference count, and iii) a self-position's reference count during each participant's trial. Users were asked not to check the route directions and their own locations as much as possible until they got lost. Note that the route directions with useful landmarks can include virtual paths indicating corresponding area landmarks. Therefore, they freely moved toward next landmarks from point/line landmarks connecting virtual paths. When calculating the distance of a virtual path, we used the distance of shortest routes between two points of the path.

We prepared three pairs of a starting point and a destination. Note that the pairs were randomly selected not to be the same routes by our method as those by Google Directions. Then we search for routes by the three methods per pair of a starting point and a destination. As a result, we got 9 routes: 3 routes using landmarks extracted based on both indirect visibility and direct visibility (LR_1 to LR_3), 3 routes using landmarks extracted based on direct visibility for only tall buildings by 3DCG-based method (VR_1 to VR_3), and 3 routes by Google Directions (GR_1 to GR_3). Finally, we evaluated 8 unique routes because LR_3 and VR_3 were the same. We conducted this study by dividing participants into groups such that each group always tested routes with different origin and destination.

3.3.2 Results

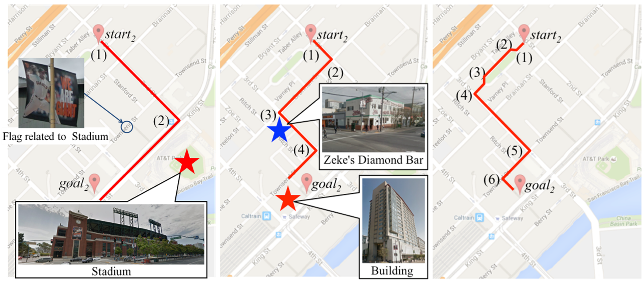
We present routes by the three methods in Figs. 3. Fig. 3 shows three routes between $start_2$ and $goal_2$: (a) LR_2 is a route with landmarks extracted by considering the three indicators of landmark's utility, VR_2 is a route with landmarks extracted by 3DCG-based method which determine direct visibility for only tall buildings, and GR_2 is a route searched by Google Directions walking mode (GR_2). On average, the landmark-based routes were simpler than routes by Google Directions on the actual road network.

In order to compare the three methods: LR, VR, and GR, we show results of the three evaluation items for routes

[*1] We asked that participants should use a cross key.

(a) Route search by LR (b) Route search by VR

Fig. 2: Images of the prototype system [3].



(a) LR_2: Indirect + Direct visibility (b) VR_2: Direct visibility (c) GR_2: Google Directions

Fig. 3: Examples of routes between $start_2$ and $goal_2$ by the three methods (LR, VR, and GR). Note that a stadium is not tall, and thus, only visible from nearby, whereas there are many cues wide spread such as flags indicated in (a).

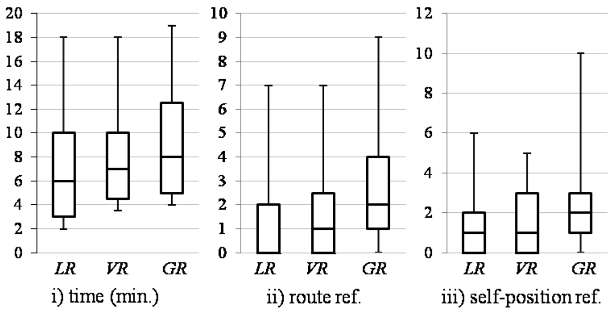


Fig. 4: Boxplots of the evaluation items for routes in SF.

as shown in Fig. 4. As a result, we found that the average time of LR was shorter than the other two methods. Furthermore, the deviation of route and self-position's reference count were smaller than others. This means that it is free from influence of a potential error due to different user's skills. In addition, the frequency of checking the self-position and route directions were decreased compared with GR. Then, significant differences (<0.05) in route directions' reference count and self-position's reference count were also observed by comparing LR to GR.

4. Conclusions

In this paper, we proposed a method to detect *useful landmarks* by measuring *visit popularity*, *indirect visibility*, and *direct visibility* by exploiting geo-tagged tweets data collected from Twitter, places and check-ins data from Foursquare, and geographical data obtained from digital maps. Having detected landmarks, we construct a route graph, which can efficiently find optimal paths in terms of the number of landmarks as well as path lengths. In the experiments, we confirm that routes with landmarks which were extracted by considering both indirect visibility and direct visibility were easier to remember and follow than the routes with landmarks which were extracted by considering direct visibility only and the routes by Google Directions, in terms of taking time from a starting point to destination, self-position's reference count, and route directions' reference count.

In the future work, we plan to test with other cities for validating the proposed approach. In addition, we will analyze tweet content in detail for extracting more semantic features of landmarks. Psychological and social analysis might be another interesting research topic.

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