Extracting POIs for Navigation based on Analyzed User Residentiality using SNS Photos

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Abstract. This paper presents a novel POI (Point of Interest) extraction method based on the residency characteristics of SNS users. Our goal is to present SNS photos of extracted POIs with high visibility and high awareness for each user on their navigation routes. In our method, we first determine the residential region of each user using geo-tagged tweets and then extract POIs at the nonresidential locations by calculating the residential users' appearance frequency based on geo-tagged tweets. This allows us to present the SNS photos of the extracted POIs by each residency characteristic on the navigation routes.

Keywords: POIs · Navigation · SNS photos · Residentality.

1 Introduction

Recently, a large amount of streaming data analysis techniques have been applied to social media and sensor data for human mobility and visualization research. Such studies tend to address the issue of extracting and identifying mobility patterns from Twitter by analyzing the content as well as the spatial and temporal aspects of individual records to infer the general movement patterns of people in a location [2, 5]. Further studies show how large-scale analysis of social media data enables us to better understand global trends in human mobility, such as the effect of season on mobility patterns and the characteristics of international travel in different nations [1] or a method to identify the trade area of a specific store (restaurant or shop) [3].

In this work, we aim to effectively provide POIs (Points of Interest) with high visibility and high awareness as destinations for visitors in navigation. Therefore, we propose a method to extract POIs based on the residentiality of SNS users by extracting regional characteristics of the crowd from tweets' locations and to present SNS photos of the extracted POIs for each visitor on the navigation routes. For this, we first detect the user ID of residential users at eight classified regions in Japan by using geo-tagged tweets. Next, we classify tweets by each user ID who lives in each region that is determined within the target region of navigation and then extracts POIs that are of interest (high awareness) for the residential users when the POIs are found to have high appearance frequency from those tweets. Finally, we efficiently acquire the geo-tagged photos around the extracted POIs and plot the selected photos including the POIs on the route to the destination inputted by the user. Overall, this paper describes our POI extraction method for each residential region and the navigation approach based on SNS photos and verifies the extraction of the POIs in the cities of Tokyo and Kyoto for each residential user.

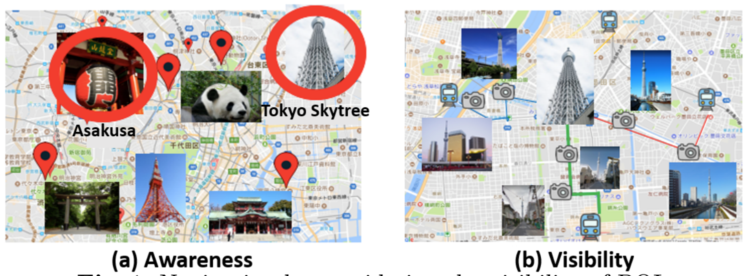

Fig. 1. Navigation by considering the visibility of POIs.

2 Extracting POIs of Residential Users for Navigation

In this work, we analyze and provide geo-tagged SNS data (e.g., text and photo) of POIs with high visibility and high awareness which could be used for navigation (see Fig. 1). As shown in Fig. 1 (a), there are many POIs in Tokyo: Asakusa's Kaminarimon has a high awareness for foreigners and the awareness of Tokyo Skytree is higher than that of Kaminarimon for Japanese people. The awareness is different for each user based on their living places and their ages. Moreover, Wakamiya et al. [4] developed a navigation system based on the visibility of POIs of each intersection by reproducing the three-dimensional streetscape from geographical data. However, there is a high cost to acquire the geographical data and to reproduce the streetscape. Therefore, our goal is to extract POIs with a high awareness of each region of residence in Japan and to extract the visibility of the extracted POIs using SNS photo data. This enables us to present SNS photos to express the visibility of POIs along the route (Fig. 1 (b)), and it can be used to support effective navigation for each user.

2.1 Extracting POIs based on Residential Users

Firstly, geo-tagged tweets were classified into eight regions based on the latitude and longitude: Hokkaido, Tohoku, Kanto, Chubu, Kinki, China, Shikoku, and Kyushu. Secondly, users duplicating from each region were extracted based on user IDs in the tweets, and the residential region of the user is defined by the largest number of the tweets for each region posted by each user. For example, a user u_i posted tweets in three regions: Tohoku, Kanto, and Chubu, the residential region of the user u_i is determined as Tohoku when the number of the user u_i's tweets in Tohoku is the largest among the three areas. Thirdly, we calculate the appearance frequency of each POI from tweets by using the following formula based on the *TF-IDF* method. We extract tweets posted by users who live in each region based on the target regions within the navigation's locations.

$$\frac{\#\text{word } w_i}{\text{total } \#\text{words from users of region } j} \cdot \log \frac{\#\text{regions}}{\#\text{regions with word } w_i} \tag{1}$$

2.2 Acquiring SNS Photos of POIs

In this paper, we collect geo-tagged SNS photos by using the Flickr API[4]. Since the collected SNS photos are used for enhancing the visibility of POIs in navigation, we assumed that the visibility of the POI is inversely proportional to the

[4] https://www.flickr.com/services/api/

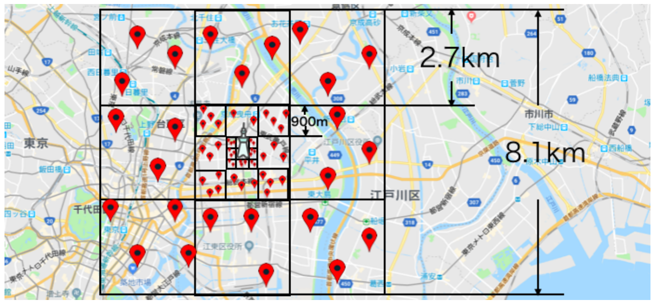

Fig. 2. Example of bounding box for acquiring SNS photos.

Table 1. Example of POIs in Tokyo and Kyoto for each residential region (Top-11)

[resident of Hokkaido at Tokyo]	1: Sensoji Temple	2: Tokyo Skytree
3: Kaminari Gate	4: Tokyo Big Sight	5: Tokyo Tower
6: The University of Tokyo	7: Venus Fort	8: Bothikoku Kokugikan
9: Hilton Tokyo	10: Tokyo Dome City	11: Tokyo Midtown
[resident of Kyushu at Tokyo]	1: Tokyo Skytree	2: Tokyo Tower
3: Chidorigafuchi	4: KITTE	5:Sensoji Temple
6: Shibuya Center Town	7: Subway Museum	8: Atre Shinagawa
9: Bothikoku Kokugikan	10: Himonya Park	11: Shibuya Hikarie
[resident of Hokkaido at Kyoto]	1: Kinkakuji	2: Kitano Tenmangu Shrine
3: Fushimi Inari Shrine	4: Kyoto Station Building	5: Miyako Messe
6: Kyoto University	7: Byodoin Temple	8: Kyoto Gyoen
9: Ginkakuji	10: Yoshida Shrine	11: Keage Incline
[resident of Kyushu at Kyoto]	1: Fushimi Inari Shrine	2: Kitano Tenmangu Shrine
3: Kyoto Municipal Museum of Art	4: Kinkakuji	5: Nanzenji
6: Miyako Messe	7: Nishiki Market	8: Kyoto University
9: Togetsu Bridge	10: Kyoto National Museum	11: Kyoto Station Building

distance to the POI and we set a bounding box based on the distance centered on the POI for acquiring photos (see Fig. 2). Many SNS photos of POIs can be acquired in the locations that are close to the POIs and since the visibility of the distant locations from the road is low, many SNS photos may become noise. Acquisition limits are a common limitation in APIs and thus this proposed method helps reduce the acquisition of "noise" SNS photos unrelated to the POIs. Then, we extract SNS photos of POIs using machine learning and plot the extracted SNS photos on the route map based on their geotags.

3 Correlation of POIs for Residential Regions

In this section, we verified the correlation of the awareness of the extracted POIs from each region by our method. In this experiment, we collected 50,000 geotagged Flickr photos of 5 POIs and 2.8 million tweets during 14 months from 2015/7 to 2016/9. In addition, we classified the tweets into eight regions and determined the residential locations of the target unique users.

3.1 Results of POI Extraction for Each Residential Region

Table 1 shows the results of the example extracted POIs in Tokyo and Kyoto by the users who live in Hokkaido (the northernmost region) and Kyushu (the southernmost region) in Japan. Tokyo Skytree and Tokyo Tower with high awareness are extracted at the top of all areas in Tokyo and temples and shrines such as Kinkakuji and Kitano Tenmangu Shrine are commonly extracted as highly recognized POIs. On the other hand, we confirmed that many POIs are unique based on the residential region such as Chidorigafuchi which is ranked third in Kyushu was not in the upper rank of other regions.

3.2 Correlation of POIs based on Regionality

In order to verify the proportion of POIs based on regionality, we calculated the Pearson correlation coefficient values using the values of the extracted POIs by Eq. (1). As a result, the average Pearson correlation coefficient values were 0.77 in Tokyo and 0.70 in Kyoto, they reached a high correlation and there were many common POIs with high awareness. On the other hand, the results show that a certain number of POIs are unique to each region. As such, to present the extracted POIs based on classified residency characteristics will be useful for awareness and pleasure navigation.

4 Conclusion and Future Work

In this work, we proposed a method to extract POIs with high awareness for visiting and sightseeing users and to present Flickr photos on navigation routes based on the visibility of the extracted POIs. The experimental results show that a certain number of POIs are unique to each region. The correlation of the POI for each region extracted from this method was found to be 0.74 on average in Tokyo and Kyoto, and it was confirmed that there were many common POIs with high awareness but a certain number of region-specific POI was also shown to exist. In the future, we plan to verify the usefulness of navigation using SNS photos of the extracted POIs through a user study.

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