Pleasant Route Suggestion based on Color and Object Rates

Shoko Wakamiya
Nara Institute of Science and Technology, Japan
wakamiya@is.naist.jp

Panote Siriaraya
Kyoto Sangyo University
Japan
spanote@gmail.com

Yihong Zhang
Kyoto University
Japan
yhzhang7@gmail.com

Yukiko Kawai
Kyoto Sangyo Univ. / Osaka Univ.
Japan
kawai@cc.kyoto-su.ac.jp

Eiji Aramaki
Nara Institute of Science and Technology, Japan
aramaki@is.naist.jp

Adam Jatowt
Kyoto University
Japan
adam@dl.kuis.kyoto-u.ac.jp

ABSTRACT

For a tourist who wishes to stroll in an unknown city, it is useful to have a recommendation of not just the shortest routes but also routes that are pleasant. This paper demonstrates a system that provides pleasant route recommendation. Currently, we focus on routes that have much green and bright views. The system measures pleasure scores by extracting colors or objects in Google Street View panorama images and re-ranks shortest paths in the order of the computed pleasure scores. The current prototype provides route recommendation for city areas in Tokyo, Kyoto and San Francisco.

CCS CONCEPTS

• **Information systems** → *Web applications*; *Recommender systems*.

KEYWORDS

Walking route recommendation, Greenery route, Panorama image, Street view, Image recognition

ACM Reference Format:
Shoko Wakamiya, Panote Siriaraya, Yihong Zhang, Yukiko Kawai, Eiji Aramaki, and Adam Jatowt. 2019. Pleasant Route Suggestion based on Color and Object Rates. In *The Twelfth ACM International Conference on Web Search and Data Mining (WSDM '19), February 11–15, 2019, Melbourne, VIC, Australia.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3289600.3290611

1 INTRODUCTION

Most of the current route recommendation systems suggest routes giving priority to efficiency such as time and distance. However, it is important to suggest routes that evoke pleasant feelings, not only for a traveler who wishes to stroll in an unfamiliar city but also for a resident who wants to enjoy commuting on foot or taking a walk to relax. Having contact with a pleasant environment such as urban greenery has a positive impact on health and well-being of individuals [1, 3]. It has been reported that unpleasant environments increase blood pressure, heart rate, muscle tension and may even contribute to immune system suppression of pedestrians. On the other hand, even short-term visits to urban green areas have positive effects on perceived stress relief [6].

In order to find routes with pleasant aspects, it would be important to explore their visual cues. To examine whether it is possible to automatically extract aesthetically-informative features of annotated city scenes, Quercia et al. [4] used crowdsourcing. The authors collected people's votes regarding beautiful, quiet, or happy qualities for street pictures taken from Google Street View and Geographvia. Then by extracting colors, edges, and visual words using image processing techniques, they identified visual cues that are generally associated with the three aesthetics' qualities. For example, it was observed that the amount of greenery was positively associated with each of the three aesthetics qualities. In [5], the authors presented a pleasant route recommendation procedure using crowd-sourced ratings assigned to street pictures and showed that reasonable proxies can be computed from Flickr tags. Zhang et al. [7] proposed a system to recommend routes that focus on visual diversity so that users can see a variety of landscapes while walking to their destination. In another example, the Scenic Planner was developed to recommend routes which contain the best scenic views by extracting relevant information from geo-tagged images from Flickr and check-ins from Foursquare [2].

This paper demonstrates a pleasant route suggestion by capturing pleasure aspects from views that could be seen when walking along a path. Assuming that a pleasant route would have much nature represented by green or brighter views, we extract two visual cues; colors and objects, by analyzing Google Street View (GSV) panorama images and measure pleasure scores of routes based on them. Note that GSV images are well distributed in many cities and are standardized compared to photos taken by users and shared online, such as in Flickr, which often contain noise (e.g., photographed people) and which tend to be clustered around sightseeing spots.

The proposed system provides three types of route ranking based on pleasure aspects; color based ranking, object based rankings, and color brightness based rankings. Specifically given a starting point s, a destination d, the number n of results to return, and a re-ranking method x, the proposed system searches for n shortest paths $\exists r \in R$ with pleasure scores measured by the specified re-ranking method x, $R_{s,d,n,x} = [(r_0, score_0^x), ..., (r_{n-1}, score_{n-1}^x)]$. Then the paths are suggested in decreasing order of their computed scores.

WSDM '19, February 11–15, 2019, Melbourne, VIC, Australia

ACM ISBN 978-1-4503-5940-5/19/02…$15.00
https://doi.org/10.1145/3289600.3290611

Our work is related to [4, 5]. However, it differs in two aspects. First, although [4] investigated colors, edges, and visual words in GSV images annotated with crowd-sourced ratings in terms of beautiful, quiet, or happy, their aim was to examine whether it is possible to automatically extract aesthetically-informative features from the annotated city scenes. Second, [5] estimated pleasant route score based on crowd-sourced ratings to panoramic images or Flickr tags, hence not the visual cues. Our contributions are threefold:

- Our system recommends pleasant routes by focusing on colors and objects that are automatically extracted from GSV panorama images by image processing.
- We estimate pleasant scores of routes in terms of color ratio, object ratio, and color brightness for re-ranking shortest paths between two points.
- We implement the pleasant route suggestion system for three cities, Tokyo, Kyoto, and San Francisco as an online web application. The system also displays color or object information of respective images on the route to let users receive evidence and investigate characteristics of each recommended route.

2 DATASETS

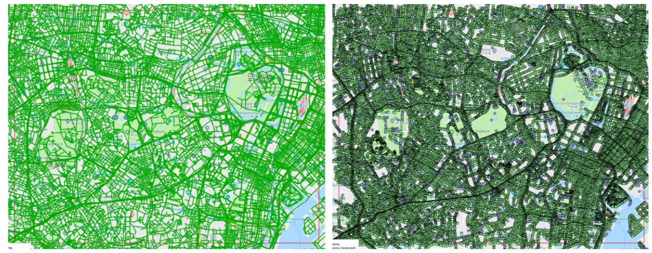
Road Network Data. To construct the road network of a city, we crawl data of the elements of OpenStreetMap (OSM)[1] such as nodes (points in space), ways (linear features and area boundaries), and relations (which denote relationships between two or more data elements). Fig. 1(a) shows the example road network in the center of Tokyo, Japan. The road network is used for crawling panoramic images explained below and searching for shortest paths.

Panoramic Image Data. To obtain information about views that could be seen when walking along a path, panoramic images from the path were collected from Google Street View (GSV). Note that GSV images are well distributed compared to Flickr images and each street in areas that we considered have at least one panorama image. When calling the GSV image API [2] with a specific location, three street view images taken with a camera heading of 0, 120, and 240 degrees, respectively are returned. The panoramic images collected at each given location are joined together. The top of Fig. 3(b) displays an example of panoramic image in Tokyo. We define the distance between a geographical point and a road as the shortest distance between the point and the street. An image is assigned to a road if it is within 10 meters from the road. We have collected the panoramic images of three city areas: Tokyo (65,141 images), Kyoto (18,957 images), and San Francisco (44,446 images). Fig. 1(b) shows the geographic distribution of panoramic images available on the streets of the central Tokyo.

3 IMAGE ANALYSIS

3.1 Extracting Color Information

To determine whether views from paths are pleasant or not, we first focus on colors of the views. We present two approaches to obtain color information from panoramic images. The first one focuses on whole colors shown in an image and the other is based on the context colors of an image such as accent color and dominant color.



(a) Road network from OSM (b) Geographic distribution of panoramic images from GSV

Figure 1: Datasets of center part of Tokyo mapped on Google Maps. (a) Road networks represented by green lines are constructed using the elements data of OpenStreetMap (OSM) and (b) the geographic distribution of panoramic images. Green dots show the locations of the panoramic images.

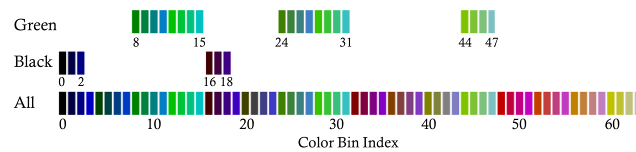


Figure 2: Classification of color bin indices into green/black.

Creating Color Histogram. One of the simplest ways to represent image colors is to extract all colors shown in an image. As it requires much cost to deal with each image's colors per pixel, a 64-dimension color histogram is created by reducing the color information. The histogram's color bin indices (0 to 63) are assigned based on the RGB triplet (r, g, b) of each image by the formula; $binindex = 16 * \frac{r}{64} + 4 * \frac{g}{64} + \frac{b}{64}$. For example, the color bin index of the color #00cc00 (r=0, g=204, b=0) would be 13. We then manually selected color bins related to green and black, respectively, in Fig. 2.

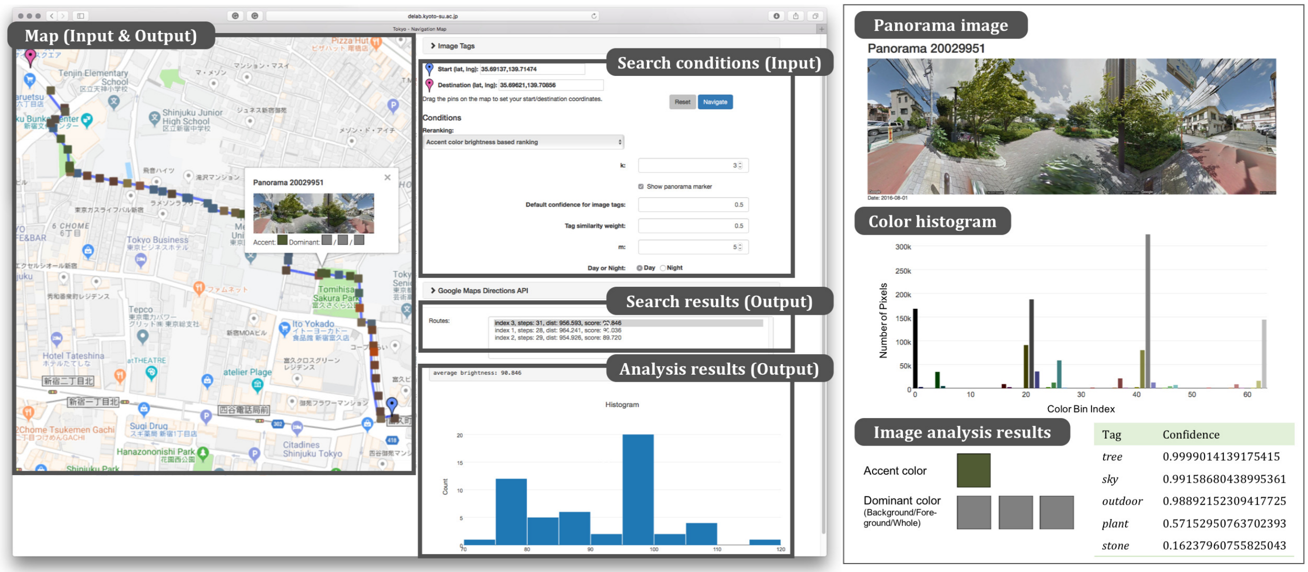
Extracting Context Color. An image analysis is applied to the panoramic images crawled as discussed in Section **??**. Given an image, the Microsoft Computer Vision API[3] returns the colors analyzed in three different contexts: foreground, background, and whole. They are grouped into twelve dominant accent colors such as black, blue, brown, gray, green, orange, pink, purple, red, etc.

3.2 Extracting Objects

To capture pleasurable aspects, it would not be enough to focus only on color information. In the image content, there can be some objects strongly related to the aspects such as "trees" and "parks".

We use such objects that can be extracted from the panoramic image content by applying image processing. Given an image, the Microsoft Computer Vision API returns a list of words called tags which are related to objects. The API also assigns a confidence score between [0, 1] to some tags, indicating how confident it is about the tags being correct. We used tags from two parts of the API results "Description" and "Tags". Although all of the tags in "Tags" have confidence scores, some of the tags in "Description" used to make the image caption do not have any confidence scores. For tags without a confidence score, we assign a default value of 0.5[4]. For the example panorama image in Fig. 3(b), five tags such as "tree", "sky", "outdoor", "plant", and "stone" are extracted with their

[1] https://www.openstreetmap.org
[2] https://developers.google.com/maps/documentation/streetview/
[3] https://azure.microsoft.com/en-us/services/cognitive-services/
[4] The value can be changed in the search conditions part in Fig. 3(a)



(a) User interface of a prototype of the navigation system (b) Detailed information of a panorama image

Figure 3: The user interface of the proposed system (a) and an example of the panoramic image analysis (b).

confidence scores. According to the reported confidence values, the first three tags have very high confidence (over 0.99).

3.3 Detecting Outdoor Panoramic Images

GSV provides panoramic images taken not only outdoors but also indoors, which are not useful for route suggestion. Hence, we also need to remove indoor images from our dataset. To select only outdoor panoramic images for route recommendation, we conducted an image classification model using TensorFlow. To build the classifier model, 1,000 images were manually classified into outdoor (742 images) and indoor (255 images). The accuracy was 93.4% when testing on 76 unlabeled images. We also found that the training data could be easily increased by exploiting object tags of panoramic images extracted in Section 3.2. Consequently 1,000 images with both "outdoor" and "street" tags were added to the set of outdoor images (1,742 images in total) and 579 images with "indoor" tag were added to the indoor set (834 images in total). Note that images which were obviously taken outdoors yet which had "indoor" tag assigned were manually removed (most of them were taken in tunnels). The final achieved accuracy was 96.7% when testing on 215 unlabeled images. Based on the result, indoor images on each route were discarded.

4 SEARCHING AND RANKING ROUTES

Given a starting point s, a destination d, and the pre-specified number n of routes to be returned, the system first finds top-n shortest paths between s and d by applying Dijkstra's algorithm. To order the paths in terms of pleasure aspects, three types of ranking methods are proposed as follows.

a) Color based ranking. This ranking re-ranks routes by considering the degree of green in panoramic images in each route. In particular, the system provides green color and black color histogram based ranking. The score is calculated by averaging the ratios of dark pixels to green pixels of respective panoramic images $p \in P_r$ for a route r: $score_r^{col} = \frac{1}{|P_r|} \sum_{p \in P_r} \frac{PixelCount(p, green)}{PixelCount(p, black)}$, where the function $PixelCount(p, color)$ returns the pixel number related to a specified color in the image p's color histogram described in Section 3.1.

b) Object based ranking. This ranking re-ranks routes based on the ratios between green objects and black/gray objects found in panoramic images of routes. In particular, the system provides two types of object based rankings as follows.

- *Green and black color tags based ranking*: The method re-ranks candidate routes in decreasing order of the ratio of black/gray objects (such as dark areas, shadows, buildings) to green objects (parks, trees, etc.) found in each route. Given all panoramic images P_r in a given route r, the ratio is calculated by considering the confidence scores of green and black/gray tags as follows.

$$score_r^{ctag} = \frac{NormTagAggregation(P_r, green)}{NormTagAggregation(P_r, (black, gray))}$$

$$NormTagAggregation(P_r, t) = (\sum_{p \in P_r} Weight(p, t))/|P_r|$$

  where $Weight(p, t)$ returns 1 if the tag t of p had the confidence value more than a threshold (we set 0.6 as the default value) and returns 0.5 as default if t of p_i did not have any confidence value assigned.
- *Manually selected tags based ranking*: This way re-ranks routes in decreasing order of the average value of manually assigned pleasure scores to tags. For this ranking, we annotated all the unique tags (512, in total) assigned to our images ("road", "water", "sky", "truck", "parking", etc.) with pleasure scores. Specifically we asked three annotators to imagine walking in a city and seeing objects represented by tags and to assign pleasure score to such tags. Each tag is given one of five scores between -2 (very unpleasant) and 2 (very pleasant). The average score $manuscore_t$

of a tag $t \in T$ is used as a weight as follows.

$$score_r^{mtag} = \frac{\sum_{t \in T} manuscore_t \times NormTagAggregation(P_r, t)}{\sum_{t \in T} NormTagAggregation(P_r, t)}$$

c) Color brightness based ranking. This ranking re-ranks routes based on the brightness of representative colors of panoramic images in each route. By representing a color obtained from an image as an RGB triplet (r, g, b), the color brightness of the image p is computed using the formula of ITU BT.709[5], $brightness_p = (0.2126 * r) + (0.7152 * g) + (0.0722 * b)$. To compute the color brightness of an image, we use two types of colors, accent color and dominant color that are extracted from each image by image processing. Note that a dominant color consists of dominant background color(s) and dominant foreground color(s). The color brightness of the route r is calculated by averaging the color brightness $brightness_p$ of all panoramic images $\forall p \in P_r$ in a given route r, $score_r^{colbr} = \frac{1}{|P_r|} \sum_{p \in P_r} brightness_p$.

This system provides two types of ranking as follows.

- *Accent color brightness based ranking*: This way re-ranks routes in decreasing order of the average of the accent color brightness.
- *Average of whole dominant colors brightness based ranking*: This re-ranks routes in decreasing order of the average value of the dominant colors brightness of all panoramic images in each route. The dominant colors brightness of an image is computed by averaging the dominant background/foreground colors.

5 DEMONSTRATION SYSTEM

Implementation. The pleasant route recommendation system has been developed and deployed as a web application as shown in Fig. 3(a). The system can be opened in a standard web browser without any need for additional software or hardware. It can be accessed online at three demo sites[6] for the city of Tokyo, Kyoto, and the central area of San Francisco. For the current implementation, we used data from OSM and GSV images. The route search by Dijkstra's algorithm was implemented using pgRouting 2.5 library [7].

When interacting with the system, users can specify a starting and a destination points within considered areas by dragging pins on the map and selecting parameters as well as choosing one of the ranking methods. They would then receive recommendations of pleasant routes between the selected points as shown in Fig. 3(a). When hovering a cursor over a node on the map, the panoramic image at the node is shown in the info window.In addition, when specifying the node, the more detailed data about the node location are available in the new window (see Fig. 3(b)). Furthermore, when selecting color brightness based ranking, small rectangles are shown on a route on the map denoting the actual accent color or dominant color in each segment of a route. These inform users about colors in different portions of a recommended route.

Example. We present a usage scenario of the proposed system in Tokyo. When a tourist who is near Meiji-jingu stadium (35.67098, 139.71688) wishes to go to Harajuku Sta. (35.67059, 139.70306), the system suggests routes re-ranked by a specified method (see Fig. 4). Just by looking at the map, Route #1 along the park would seem

[5] https://www.itu.int/rec/R-REC-BT.709/en

[6] http://delab.kyoto-su.ac.jp/nav/*/map. Please replace '*' as 'tokyo', 'kyoto', or 'sf'

[7] https://docs.pgrouting.org/2.5/en/index.html

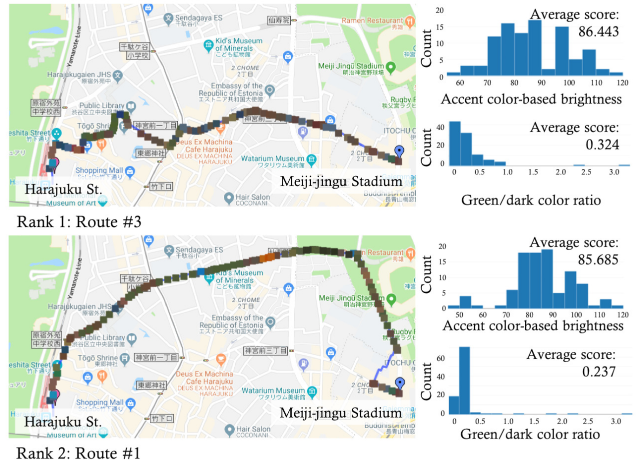


Figure 4: Routes suggested by accent color brightness based ranking (left). Right side graphs show the brightness histogram and green/dark color ratio.

to have much more pleasant views. However, our system ranked Route #3 at the top by exploiting visual cues of panorama views. According to the image analysis results (the histogram of accent color-based brightness and that of green/dark color ratio) this route has more brighter colors and better green/dark color ratio.

6 CONCLUSIONS

A pleasant environment is known to positively affect human well-being and health. This paper demonstrated a pleasant route recommendation system, which provides routes which have more nature or brighter views in terms of colors or objects extracted from Google Street View panorama images by applying image analysis. The computed shortest paths are ranked in the order of their pleasure scores, which were measured based on color ratio, object ratio, and color brightness. The proposed route recommendation system is available as an online web application. The system could be extended by adding more cities in the future.

ACKNOWLEDGMENTS

This work was partially supported by MIC SCOPE #171507010, JSPS KAKENHI Grant Numbers JP16K16057 and JP16H01722.

REFERENCES

[1] H. Bixby, S. Hodgson, L. Fortunato, A. Hansell, and D. Fecht. 2015. Associations between Green Space and Health in English Cities: An Ecological, Cross-Sectional Study. *PLOS ONE* 10, 3 (03 2015), 1–12.

[2] C. Chen, X. Chen, Z. Wang, Y. Wang, and D. Zhang. 2017. ScenicPlanner: planning scenic travel routes leveraging heterogeneous user-generated digital footprints. *Frontiers of Computer Science* 11, 1 (2017), 61–74.

[3] M. C. Kondo, J. M. Fluehr, T. McKeon, and C. C. Branas. 2018. Urban Green Space and Its Impact on Human Health. *International Journal of Environmental Research and Public Health* 15, 3 (2018).

[4] D. Quercia, N. K. O'Hare, and H. Cramer. 2014. Aesthetic Capital: What Makes London Look Beautiful, Quiet, and Happy?. In *Proc. of CSCW*. 945–955.

[5] D. Quercia, R. Schifanella, and L. M. Aiello. 2014. The shortest path to happiness: Recommending beautiful, quiet, and happy routes in the city. In *Proc. of HT*. 116–125.

[6] L. Tyrväinen, A. Ojala, K. Korpela, T. Lanki, Y. Tsunetsugu, and T. Kagawa. 2014. The influence of urban green environments on stress relief measures: A field experiment. *Journal of Environmental Psychology* 38 (2014), 1–9.

[7] Y. Zhang, P. Siriaraya, Y. Wang, S. Wakamiya, Y. Kawai, and A. Jatowt. 2018. Walking Down a Different Path: Route Recommendation Based on Visual and Facility Based Diversity. In *Companion Proc. of WWW*. 171–174.