Visual Navigation with Street View Image Matching

Chih-Hung Hsu[1] and Huei-Yung Lin[2]
[1]*Department of Electrical Engineering, National Chung Cheng University, 168 University Rd., Chiayi 621, Taiwan*
[2]*Department of Electrical Engineering, Advanced Institute of Manufacturing with High-Tech Innovation, National Chung Cheng University, 168 University Rd., Chiayi 621, Taiwan*

Keywords: Visual Navigation Assistance, Image Matching, Panoramic Image.

Abstract: The vision based navigation approach is a key to success for the driving assistance technology. In this work, we presents a visual navigation assistance system based on the geographic information of the vehicle and image matching between the online and pre-established data. With the rough GPS coordinates, we utilize the image retrieval algorithms to find the most similar image in the panoramic image database. The searching results are then compared with the input image for feature matching to find the landmarks in the panoramic image. By using the 360° field-of-view of the panoramic images, the camera's heading can be calculated by the matching results. Finally, the landmark information is identified by the markers on the Google map as visual guidance and assistance.

1 INTRODUCTION

The navigation techniques based on visual information are getting more and more popular in recent years. When people are in an unknown or unfamiliar environment, visual navigation plays a key role to the movement guidance. In general, landmarks are the most reliable visual cues for the perception of outdoor scenes. Using landmarks as references is very obvious to understand where you are and where do you want to go. In the traditional navigation systems, a number of available landmarks are tagged on the map and their images are provided for location identification. Since the landmarks may appear differently observed from different viewing directions, scene recognition becomes a nontrivial task if the images are captured perspectively from a single viewpoint.

Currently, it is still not possible to achieve the fully autonomous navigation due to various technical difficulties. Thus, many researchers are devoted themselves to the assisted technologies for navigation. The previous work on the development of assisted navigation techniques is generally divided to two categories for the indoor and outdoor applications. In the indoor case, Saab *et al.* use the radio frequency identification device (RFID) for localization (Saab and Nakad, 2011). Several passive tags are pre-installed in the indoor environment, and the RFID device can retrieve the information from the tags when a user gets close to those places. Mulloni *et al.* utilize the image marker to encode the information in the proposed system (Mulloni et al., 2009). The users can use their cell phones to capture and decode the markers to determine the locations. Huang *et al.* present a vision based self-localization technique for mobile robot applications (Huang et al., 2012). A camera is used to capture the images of pre-installed 2D barcode patterns on the ceiling for indoor localization. The above approaches require structured or controlled environments to derive the location information and therefore are not suitable for the outdoor applications.

For the outdoor navigation, a primary information source can be obtained from the images of the scenes. The images are capable of providing the visual assistance close to the human perception while not altering the environment. There have been many techniques developed to construct the object classifiers (i.e., trees, cars, buildings, roads, pedestrian, etc.) and used to process the input scene images for the derivation of semantic maps. The most likely scenes in the image database are then identified according to the semantic maps (Wang et al., 2015; Yao et al., 2014; Siddiqui and Khatibi, 2014). Some researchers assume that the users are able to capture the most representative objects such as buildings and define them as landmarks. The navigation system is designed to use the input image to match and find the related land-

Hsu, C-H. and Lin, H-Y.
Visual Navigation with Street View Image Matching.
DOI: 10.5220/0005674405830589
In *Proceedings of the 11th Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2016) - Volume 3: VISAPP*, pages 585-591
ISBN: 978-989-758-175-5

mark image and return the corresponding information to the users. Two commonly adopted methods, including image retrieval and landmark matching, are briefly reviewed as follows.

The image retrieval approach is based on the image features like texture, line, shape, etc. Turcot *et al.* use the bag-of-words to construct an image database, and choose the most useful features for image retrieval (Turcot and Lowe, 2009). Philbin *et al.* adopt the random tree to construct the relationship between the image and the image features, and then use it for image retrieval (Philbin et al., 2007). Hu *et al.* propose a gradient field HOG (GF-HOG) technique. The users sketch the shapes of objects and the system can extract the GF-HOG features to perform the image retrieval (Hu and Collomosse, 2013). In the recent years, the GPS system is extensively used in many applications. Some researches also utilize the GPS data to increase the accuracy of image retrieval (Chen et al., 2011; Altwaijry et al., 2014; Zamir and Shah, 2010; Liu et al., 2012).

In the landmark matching techniques, Naoyuki *et al.* use SURF (Speeded Up Robust Features) (Bay et al., 2008) to perform image matching between the panoramic and perspective images (Uchiyama et al., 2009). However, due to the 360-degree field-of-view (FOV) of the panoramic images, good results cannot be achieved using the traditional image features (Lin et al., 2013). Chen *et al.* crop the landmarks in the panoramic image to many blocks, calibrate these sub-image blocks, and then use these sub-images to match with the input image (Chen et al., 2011). Similarly, the traditional 2D orientation descriptor such as SIFT (Scale Invariant Feature Transform) is also unsuitable for panoramic image because of the image distortion and camera rotation (Lowe, 2004). Benjamin *et al.* propose a 3D orientation SIFT and use it to improve the matching results for panoramic images (Resch et al., 2014).

In the past few years, Google Map Street View could be the most famous image guided navigation system. The users only need to input theirs GPS coordinates, and the system will quickly return the locations on the map and the surrounding 360-degree images. Since the GPS accuracy is occasionally affected by the weather condition and other factors, the users should manually check the images are correct or not. In this work, we present a visual navigation assistance system. The user only have to input a landmark image and the nearby GPS coordinates, the proposed navigation system is able to return the name of the identified landmark. Due to the advances of smart wearable devices, it becomes possible to obtain the GPS enabled images easily. Our navigation assistance technique utilizes the image and geographical information to search in the panoramic image database. Since the panoramic image contains 360° FOV, the matching result can be used to calculate the heading of the image capture orientation. The corresponding landmark marker is then obtained by searching the Google map images with the heading angle.

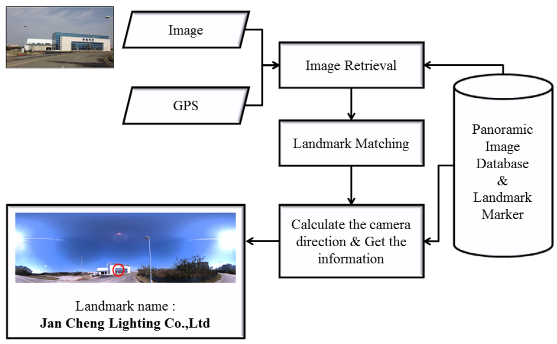


Figure 1: An overview of the proposed visual navigation assistance framework.

2 PROPOSED FRAMEWORK

The proposed framework consists of three stages: (i) image retrieval from the panoramic image database, (ii) image matching between the perspective and panoramic images, (iii) calculation of the camera heading and using the angle to search the landmark marker on the Google Map. The overview of our system is shown in Figure 1. We will describe the method used in detail below.

2.1 Database and Image Retrieval

In the proposed navigation technique, several image databases are first recorded in different regions. Each image database consists of panoramic images and the associated geographical coordinates. For testing or vehicle localization, we capture the perspective images using a conventional camera and also record the geographical information around the regions. The test images are acquired with the landmarks we are interested for navigation assistance.

For an input perspective image, our navigation system should identify the most similar panoramic image in an image database. Since our database contains images and the associated geographical coordinates, there are two simple ways to perform the image retrieval– using either the image based techniques or the GPS information. These two methods, however, both have some drawbacks. First, using the image

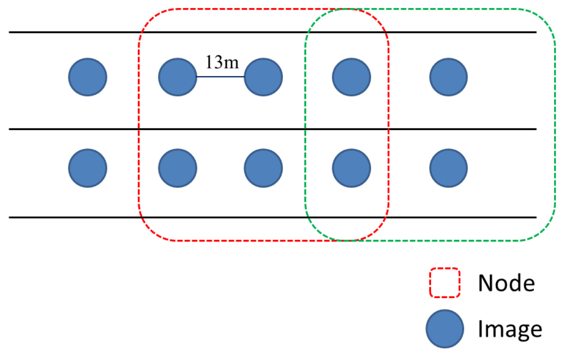


Figure 2: The nodes assigned by the images in the database.

based technique alone will require a lot of searching time since there usually have many street scene images in the database. Second, the GPS information is not always reliable because it may be affected by some factors, such as bad weather conditions, tall building, tunnel, etc.

Our navigation assistance technique combines the image based approach and geographical coordinates to construct the image retrieval system. We capture the panoramic images on the left and right lanes along a road for every 13 meters. A node is assigned to 6 neighboring panoramic image capture locations as illustrated in Figure 2. The nodes of 6 images plus 2 additional ones in the front and 2 additional ones in the back are used for image retrieval and there is no need to record the GPS coordinates for each panoramic image. Given an input image, its location will be associated with a nearest node which is verified by feature matching on the panoramic images in the database.

In the previous research, it is shown that SIFT outperforms other features (Juan and Gwun, 2009). When the 10 candidate panoramic images are found, the number of SIFT matching points is considered as the similarity measure between the panoramic and input images. We extract the SIFT feature points in the input image and 10 candidate panoramic images. The features of candidate images are merged to a feature vector

$$F = \{f_1, f_2, f_3, f_4, f_5, f_6, f_{pre1}, f_{pre2}, f_{back1}, f_{back2}\}$$

The feature vector F is used to match with the input image feature f_I. A score is given to each panoramic image according to the number of matching feature points. The panoramic image which has the highest score is the most similar to input image. Mathematically, it can be written as

$$\{S_1, \ldots, S_6, S_{pre1}, S_{pre2}, S_{back1}, S_{back2}\} = M(f_I, F)$$

$$I_r = \arg\max M(f_I, F)$$

where I_r is the retrieved panoramic image.

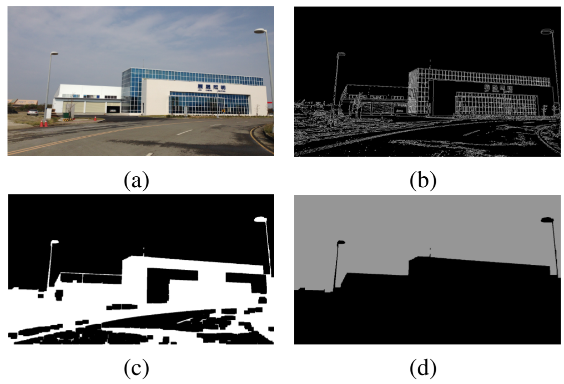


Figure 3: The image segmentation to separate the sky and landmark regions. (a) The original image. (b) The edge image obtained by Canny edge detection. (c) The result from dilation and erosion. (d) The segmentation result by the FloodFill algorithm.

2.2 Landmark Matching

Although the most similar image is found in the image retrieval stage, the system still does not know the corresponding landmark in the panoramic image. The SIFT features are commonly used for landmark matching, but the results we find are generally not good enough. There always exist some incorrect matching points. Since the landmarks of interests usually contain regular appearance, we add landmark contour line features to enhance the correctness of SIFT feature matching. It is the common case that the landmarks in the images are connected with the sky. Thus, the landmark contour lines can be obtained by separating the sky region from the foreground. We use the segmentation method proposed by Laungrungthip *et al.* (Laungrungthip et al., 2008). Canny edge detection (Canny, 1986) is first applied to extract the line segments, followed by the dilation and erosion operations to fill the gaps in broken edges. The FloodFill algorithm is then carried out to fill the region from the top of the image (Hughes et al., 2013). Finally, the landmarks are separated from the sky by the contour lines detected by Hough transform (Hough, 1962).

In the outdoor scenes, the captured images usually contain a lot of trees and leaves. These objects should be treated as noise because it will cause unreliable landmark matching. In general, the line segments associated with trees and leaves have smaller length and the most representative line segments have longer length. According to this property, the noise is filtered out by comparing the length of line segments. We can then choose the longest line segments at different angles to be the most representative ones. The generation of line segments is based on the fact that

Figure 4: The ROI setting for the feature descriptor construction.

there is a significant color change on both sides of the line. If we choose two ROIs from each side of a line (as shown in Figure 4) and consider these ROIs as a single region, its histogram will have two peak values– associated with the sky and the landmark, respectively.

We construct the feature descriptor of a line segment according to the properties, and denote it as a 13-dimensional feature vector

$$F_d = [\, L_d, H_{max1}, H_{max2}, V_{max1}, V_{max2}, H_{avg1}, H_{avg2}, V_{avg1}, V_{avg2}, D_{v\_max}, D_{v\_avg}, H_{sd1}, H_{sd2} \,]$$

where L_d is the angle of of the line, H_{max} and V_{max} are the peak values of the hue and intensity histograms of the ROIs, H_{avg} and V_{avg} are the average values of the hue and intensity histograms of the ROIs, D_{v_max} and D_{v_avg} are the difference of the ROI's maximum and average values, H_{sd} is the standard deviation. The feature descriptor is used to match the line segments between the input and panoramic images. We use L_d to filter out the segments which have a large difference of line angles, and calculate the Euclidean distance using the rest 12 parameters.

There are usually many matched line segments and the number should be further reduced. In this stage, the segments with the top 3 similarity scores are chosen as candidates. Any two line segments in the input image will be merged if the distance between their midpoints is smaller than a threshold. The midpoint of the merged line segment is then considered as a possible representative of landmark regions. Thus, the SIFT feature points far away from those midpoints are discarded as they might be incorrect matches. Due to the lighting condition or other imaging issues of the outdoor scenes, occasionally the line features are not very reliable and the true SIFT matches are not close to the midpoints of line segments. To deal with this problem, we check the number of SIFT matches which are close to the midpoints. If the proportion is less than 1/3, then the line features will not be used to filter out the SIFT matching points.

2.3 Camera Heading and Landmark Information

In the previous section, the most correct SIFT matches are recorded. The k-means algorithm is then utilized to cluster the SIFT features, and the landmark in the panoramic image is identified by the cluster with the most SIFT points. If the perspective image is captured when facing the landmark, then the cluster's location in the panoramic image can be used to determine the camera heading. We convert the heading to an angle D_c between 0 and 360 degrees by

$$D_c = \frac{360}{L_I}(P_c - P_n) \tag{1}$$

where P_c is the x-coordinate of the cluster's center in the panoramic image, P_n is the north direction in the images we record in the database, and L_I is the image width.

The system will collect all of the landmark markers we have constructed on Google Map if the distance is less than 90 meters to the input image location, and and record all angles D_L between the input location and the landmarks (see Figure 5), i.e.,

$$D_L = \{D_1, D_2, \ldots, D_n\}$$

where n is the number of landmark. We choose a marker M_L with the property that the angle difference between D_c and D_L is the smallest and given by

$$M_L = \arg\min |D_c - D_n|$$

The landmark information can then be derived from the associated marker on Google Map.

3 EXPERIMENTS

Our visual navigation assistance technique is evaluated on 4 databases captured with a Point Grey Ladybug2 omnidirectional camera and input images acquired from a smart phone. The geographic information of the database and input images are obtained

Figure 5: The camera heading angle between the current location and the marker.

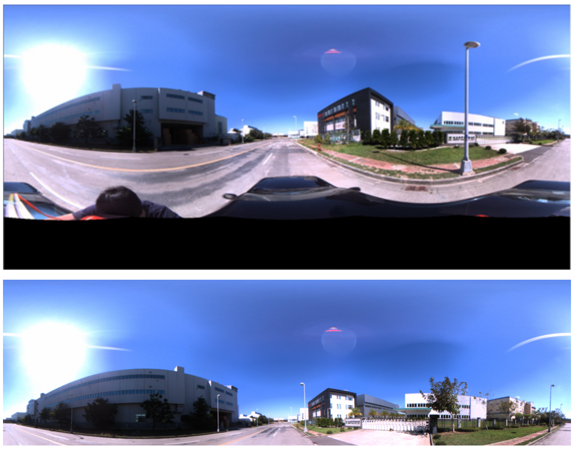


Figure 6: An example of the panoramic image in the database. Top: the original image. Bottom: the cropped image and used for landmark identification.

from a GPS receiver and the built-in GPS module of the mobile phone, respectively. The Ladybug2 omni-directional imaging system consists of 6 wide angle cameras. Six individual images captured by Ladybug2 are stitched to form a single panoramic image with the resolution of 2048×1024. Since the lower part of street scene panoramic images is less important for landmark detection, the images are further cropped to the resolution of 2048×598 with the upper part remained (see Figure 6). The input image captured by the mobile phone has the resolution of 3624×2448. To reduce the computation time, the images are resampled to the resolution of 1088×816 for processing.

Four image databases used in the experiments are constructed with different geographic regions. The detail information is shown in the Table 1 with the total distance, the numbers of images, nodes and landmarks. The navigation system graphical user interface is shown in Figure 7. Given an input perspective image acquired by a mobile camera, it will return the most similar panoramic image in the database and draw a red circle as the camera heading derived from the image. The circle location is P_c as used in Eq. (1). In the navigation system, the name of the landmark is also provided according to the marker identified on Google Map.

Table 1: The numbers of node, image and landmark obtained from the datasets.

	Set 1	Set 2	Set 3	Set 4
Distance (m)	673	375	1060	286
# of Node	27	14	41	12
# of Image	29	19	51	15
# of Landmark	4	5	9	3

3.1 Runtime Discussion

We test our navigation assistance system on a Windows 7, 32bit PC with 4GB RAM and an Intel Core i5 CPU. The run time of the proposed technique is tabulated in Table 2 with processing stages. The total execution time for all processes is 8 seconds per image. Due to the image retrieval stage using 10 high resolution panoramic images (2048×598), it spends most execution time in the process and make it the bottleneck of our system.

Table 2: The computation time for each processing stage and the overall execution time.

Process	Time (s)
Image retrieval	4.14
Extract SIFT features (query)	0.43
Extract SIFT features (dataset)	0.48
Extract line feature (query)	0.38
Extract SIFT feature (dataset)	0.47
Total execution time	8

3.2 Experimental Results

We first compare the landmark matching results. In our system, we use line features to filter out the incorrect SIFT matching points. As illustrated in Figure 8, the matching results of the input and panoramic images are shown with different methods. The top image in Figure 8(b) shows the result only using the SIFT features to match the input image. The small red circles represent the matching points. It can be seen that there are some incorrect SIFT matches which do not correspond to the landmark's nearby regions in Figure 8(a). If the line features are incorporated as shown in the bottom of Figure 8(b), most of the wrong SIFT correspondences are eliminated successfully. The camera heading of Figure 8(a) is then identified correctly.

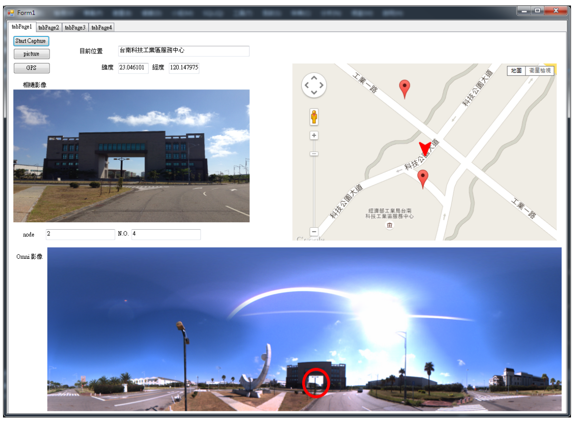
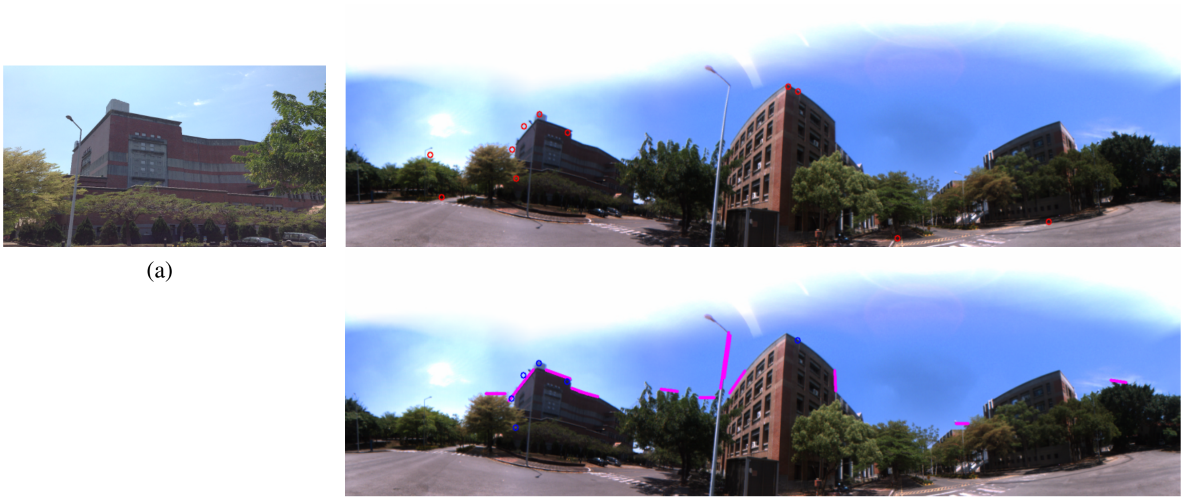


Figure 7: The graphical user interface of the visual navigation assistance system.



(a)

(b)

Figure 8: The results of two landmark matching approaches. The right top result only adopt SIFT to match the landmark. The right bottom result uses the additional line feature.

To evaluate the system performance, two important criteria for navigation assistance are adopted, namely the correctness of landmark's name and camera's heading direction. The camera heading is drawn in the user interface and indicated by a red circle (say, C_a). Its correctness is verified by the overlap with the landmark area (say, P_l) in the panoramic image, i.e., $C_a \cap P_l$. Our technique is compared with the methods proposed by Guan *et at.* (Guan et al., 2014) and Bettadapura *et al.* (Bettadapura et al., 2015) for performance evaluation. Due to the objectives of their works are not completely the same as ours. Only the part of their frameworks related to image retrieval and navigation results is used for comparison. The system accuracy is computed using our formulation.

The image features derived from their methods are adopted to calculate the camera heading using Eq. (1), and the landmark's name is obtained from the corresponding marker in Google Map. In (Guan et al., 2014), the geographic information and SURF features are adopted for image retrieval on a pre-constructed image database. Bettadapura *et al.* use the geographic information to retrieve the image. The maximally stable extremal region (MSER) is extracted to detect candidate points, and SIFT is used to describe the feature points. Table 3 shows the accuracy of our approach and these two methods performed on each datasets.

Table 3: The performance comparison with other methods.

	Set 1	Set 2	Set 3	Set 4
Our method	79.3%	78.9%	96%	80.0 %
Guan	58.6%	63.2%	76.4%	60.0%
Bettadapura	24.5%	24.1%	47.0%	33.3%

The average accuracy of our results on the datasets is 83.6%, which is better than those obtained from the other two methods. Some of our false navigation results are the incorrect camera headings. It is due to the encoding error on x-coordinates in the panoramic images. In (Guan et al., 2014) and (Bettadapura et al., 2015), they both use the gyroscopic compass to improve the performance of their systems. However, our technique aims to use only the images and geographic information to construct the visual navigation assistance. Although the gyroscopic compass can provide more correct camera headings in the previous works, our system has better matching results in small objects like monuments or road signs.

4 CONCLUSIONS

In the paper, we propose a visual navigation assistance system using the geographic information and image matching. Our technique has been tested on the real scene images and provides 83.55% accuracy in four image datasets. In addition to the results are better than the previous approaches, the proposed method is also capable of landmark recognition without training. The future work will focus on the integration with Google Map Street View. With the advances of wireless communication, the Google street view image database can be accessed in real-time. The wearable devices will also be tested to emphasize the portability of the presented technique.

ACKNOWLEDGMENTS

The support of this work in part by the National Science Council of Taiwan under Grant NSC-102-2221-E-194-019 is gratefully acknowledged.

REFERENCES

Altwaijry, H., Moghimi, M., and Belongie, S. (2014). Recognizing locations with google glass: A case study. In *Applications of Computer Vision (WACV), 2014 IEEE Winter Conference on*, pages 167–174.

Bay, H., Ess, A., Tuytelaars, T., and Van Gool, L. (2008). Speeded-up robust features (surf). *Comput. Vis. Image Underst.*, 110(3):346–359.

Bettadapura, V., Essa, I. A., and Pantofaru, C. (2015). Egocentric field-of-view localization using first-person point-of-view devices. In *2015 IEEE Winter Conference on Applications of Computer Vision, WACV 2014, Waikoloa, HI, USA, January 5-9, 2015*, pages 626–633. IEEE Computer Society.

Canny, J. (1986). A computational approach to edge detection. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 8(6):679–698.

Chen, D. M., Baatz, G., Koser, K., Tsai, S. S., Vedantham, R., Pylvanainen, T., Roimela, K., Chen, X., Bach, J., Pollefeys, M., Girod, B., and Grzeszczuk, R. (2011). City-scale landmark identification on mobile devices. In *Proceedings of the 2011 IEEE Conference on Computer Vision and Pattern Recognition*, CVPR '11, pages 737–744, Washington, DC, USA. IEEE Computer Society.

Guan, T., Fan, Y., Duan, L., and Yu, J. (2014). On-device mobile visual location recognition by using panoramic images and compressed sensing based visual descriptors.

Hough, P. V. (1962). Method and means for recognizing complex patterns. US Patent 3,069,654.

Hu, R. and Collomosse, J. (2013). A performance evaluation of gradient field hog descriptor for sketch based image retrieval. *Comput. Vis. Image Underst.*, 117(7):790–806.

Huang, W.-T., Tsai, C.-L., and Lin, H.-Y. (2012). Mobile robot localization using ceiling landmarks and images captured from an rgb-d camera. In *Advanced Intelligent Mechatronics (AIM), 2012 IEEE/ASME International Conference on*, pages 855–860.

Hughes, J. F., van Dam, A., McGuire, M., Sklar, D. F., Foley, J. D., Feiner, S. K., and Akeley, K. (2013). *Computer graphics: principles and practice (3rd ed.)*. Addison-Wesley Professional, Boston, MA, USA.

Juan, L. and Gwun, O. (2009). A comparison of sift, pca-sift and surf. *International Journal of Image Processing (IJIP)*, 3(4):143–152.

Laungrungthip, N., McKinnon, A., Churcher, C., and Unsworth, K. (2008). Edge-based detection of sky regions in images for solar exposure prediction. In *Image and Vision Computing New Zealand, 2008. IVCNZ 2008. 23rd International Conference*, pages 1–6.

Lin, H., Lin, Y., and Yao, J. (2013). Scene change detection and topological map construction using omnidirectional image sequences. In *Proceedings of the 13. IAPR International Conference on Machine Vision Applications, MVA 2013, Kyoto, Japan, May 20-23, 2013*, pages 57–60.

Liu, H., Mei, T., Luo, J., Li, H., and Li, S. (2012). Finding perfect rendezvous on the go: Accurate mobile visual localization and its applications to routing. In *Proceedings of the 20th ACM International Conference on Multimedia*, MM '12, pages 9–18, New York, NY, USA. ACM.

Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *Int. J. Comput. Vision*, 60(2):91–110.

Mulloni, A., Wagner, D., Barakonyi, I., and Schmalstieg, D. (2009). Indoor positioning and navigation with camera phones. *Pervasive Computing, IEEE*, 8(2):22–31.

Philbin, J., Chum, O., Isard, M., Sivic, J., and Zisserman, A. (2007). Object retrieval with large vocabularies and fast spatial matching. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 1–8.

Resch, B., Lang, J., and Lensch, H. (2014). Local image feature matching improvements for omnidirectional camera systems. In *Pattern Recognition (ICPR), 2014 22nd International Conference on*, pages 918–923.

Saab, S. and Nakad, Z. (2011). A standalone rfid indoor positioning system using passive tags. *Industrial Electronics, IEEE Transactions on*, 58(5):1961–1970.

Siddiqui, J. and Khatibi, S. (2014). Semantic urban maps. In *Pattern Recognition (ICPR), 2014 22nd International Conference on*, pages 4050–4055.

Turcot, P. and Lowe, D. (2009). Better matching with fewer features: The selection of useful features in large database recognition problems. In *Computer Vision Workshops (ICCV Workshops), 2009 IEEE 12th International Conference on*, pages 2109–2116.

Uchiyama, H., Saito, H., Servieres, M., and Moreau, G. (2009). Image based view localization system retrieving from a panorama database by SURF. In *Proceedings of the IAPR Conference on Machine Vision Applications (IAPR MVA 2009), Keio University, Yokohama, Japan, May 20-22, 2009*, pages 118–121.

Wang, S., Wang, Y., and Zhu, S.-C. (2015). Learning hierarchical space tiling for scene modeling, parsing and attribute tagging. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, PP(99):1–1.

Yao, C.-W., Cheng, K.-S., and Lin, H.-Y. (2014). A vision assisted vehicle navigation technique based on topological map construction and scene recognition. In *Advanced Video and Signal Based Surveillance (AVSS), 2014 11th IEEE International Conference on*, pages 399–404.

Zamir, A. R. and Shah, M. (2010). Accurate image localization based on google maps street view. In *Proceedings of the 11th European Conference on Computer Vision: Part IV*, ECCV'10, pages 255–268, Berlin, Heidelberg. Springer-Verlag.