Mobile Panoramic Vision for Assisting the Blind via Indexing and Localization

Feng Hu[1], Zhigang Zhu[2], Jianting Zhang[2]

[1]Department of Computer Science, Graduate Center, The City University of New York, United States
[2]Department of Computer Science, City College and Graduate Center, The City University of New York, United States

Abstract. In this paper, we propose a first-person localization and navigation system for helping blind and visually-impaired people navigate in indoor environments. The system consists of a mobile vision front end with a portable panoramic lens mounted on a smart phone, and a remote GPU-enabled server. Compact and effective omnidirectional video features are extracted and represented in the smart phone front end, and then transmitted to the server, where the features of an input image or a short video clip are used to search a database of an indoor environment via image-based indexing to find both the location and the orientation of the current view. One-dimensional omnidirectional profiles, which capture rich vertical lines and additional features in both HSI and HSI gradient space, are used in the database modeling step for constructing the model of an indoor environment from its panoramic video sequences. In the navigation step, the same type of features of a short video clip, are used as key words for searching in the database in order to provide candidate of the possible locations of the user and then estimate the orientation of the current view. To deal with the high computational cost in searching a large database for a realistic navigation application, data parallelism and task parallelism properties are identified in the database indexing steps, and computation is accelerated by using multi-core CPUs and GPUs. Experiments on synthetic data and real data are carried out to demonstrate the capacity of the proposed system with respect to real-time response and robustness.

Keywords: Panoramic Vision, Mobile and Cloud Computing, Blind Navigation

1 Introduction

Localization and navigation in indoor environments such as school buildings, museums etc., is one of the critical tasks a visually-impaired person faces for living a convenient and normal social life[5].Despite a large amount of research havebeen carried out for robot navigation in robotic community[6], and several assistive systems are designed for blind people[14][10][1], efficient and effective portable solutions for visually impaired people are still not available. In this paper, we

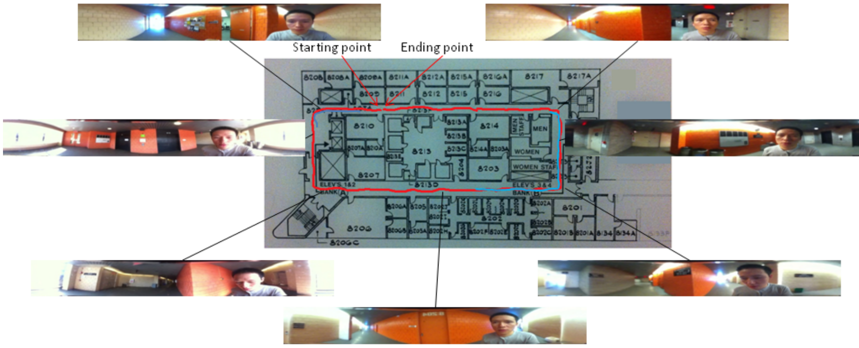


Fig. 1: One testing environment and some sample omnidirectional images. The red line in the map is the modeled path, and the dark blue line as well as the light blue line are the testing paths

intend to build an easy-to-use and robust localization and navigation system for visually-impaired people. Currently, the main stream solutions for localization are based on GPS signals; however, in an indoor environment these methods are not applicable since GPS signals are unavailable or inaccurate. Pose measurements using other onboard sensors such as gyroscopes, pedometers, or IMUs, are not precise enough to provide user heading information and instructions for moving around for a visually impaired person.

To provide an alternative solution to GPS-based navigation system, RFID sensors and mobile robot based systems were developed by Kulyukin et al[8] and Cicirelli et al[3]. Although these passive RFID tags can integrate local navigation measurements to achieve global navigation objectives, the system relies heavily on the distribution of RFID sensors and the specially designed robot. In our method, no extra sensors or infrastructure need to be installed in the environment, and no other complex devices are required except a daily-used smart phone (such as an iPhone) and a compact lens. Another existing solution proposed by Legge et al[9] uses a handheld sign reader and widely distributed digitally-encoded signs to give location information to the visually impaired. Again, this method also requires attaching new tags to the environment, and it can only recognize some specific locations. Our proposed system does not have any requirements for changing the environment, and the viewer can be localized in the entire interiors of a building instead just of a few individual locations.

In contrast to previsou methods[8][9], our system has the following characteristics that make it an appropriate assistive technology for the visually impaired navigation in the indoor context. (a) No extra requirements are needed on hardware except a daily-used smart phone and a portable lens, which is simple, inexpensive and easy to operate. No extra power supply is needed either. (b) A cloud computing solution is utilized. Only compact features of a video clip are needed to be processed in the front end and then be transmitted to a server, which guarantees a real-time solution while saving a lot of bandwidth. Different from transmitting an original image or a video clip, which will cost a lot of mobile traffic and may need a long communication time, our method only transfers essential scene features, usually less than one percent of the original data and thus has very low communication cost and little transmitting time. (c) The system is scalable. Majority of localization and navigation algorithms are executed in the cloud server part, and the databases are stored in the cloud part too. This efficiently makes good use of the storage and computation power of the server and do not occupy too much of smart phone's resources. It also indicates that the solution can scale up very well for a large database. (d) Parallelism in both data and tasks can be explored, since data parallelizing can be applied in both spatial and temporal dimensions of the video data, the localization algorithms can be accelerated by using multi-core GPUs, and thus significantly reducing computational time. One example of our testing environments is shown in Fig. 1. The map in the middle is a indoor floor plan of a campus building. The red line in the map is the path for modeling this environment, and the dark blue line as well as the light blue line are the paths used for testing. Some sample omnidirectional images are shown around the map, and their geo-locations are attached to the floor plan.

The organization of the rest part of the paper is as follows. Section 2 discusses related work. Section 3 explains the main idea of the proposed solution and describes the overall approach. Section 4 illustrates the calibration and preprocessing procedure. Section 5 discusses localization by indexing as well as issues in paralleling process. Section 6 gives a conclusion and points out the possible future work.

2 Related Work

Appearance-based localization and navigation has been studied extensively in computer vision and robotics communities using a large variety of different methods and camera systems. Outdoor localization in the urban environment with panoramas captured by a multicamera system (with 5 side cameras) mounted on the top of a vehicle is proposed by Murillo et al[13]. Another appearance approach based Simultaneous Localization and Mapping (SLAM) on large scale road database, which is obtained by a car-mounted sensor array as well as GPS, is proposed by M. Cummins and P. Newman[4]. These systems deal with outdoor environment localization with complex camera systems. In our work, we focus on the indoor environment with simple but effective mobile sensing devices (smart phone + lens) to serve the visually-impaired community by providing a robust and easy-to-use panoramic mobile navigation system.

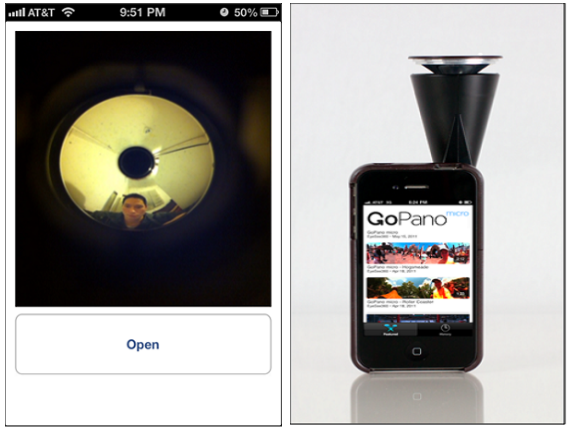
Visual nouns based orientation and navigation system for blind people was proposed by Molina et al[11][12], which aligns images captured by a regular camera into panoramas, and extracts three kinds of visual nouns features (signage, visual text, and visual-icons) to give location and orientation instructions

Fig. 2: System diagram

to the visually-impaired people using visual noun matching and PnP localization methods. In their work, obtaining panoramas from images requires several capture actions and relatively large computation resources. Meanwhile, sign detection and text recognition procedures face a number of technical challenges in a real environment, such as illumination changes, perspective distortion, and poor image resolution. In our paper, an omnidirectional lens GoPano[7] is used to capture panorama images in real time, and only one shot is needed to capture the entire surroundings rather than multiple captures. No extra image alignment process is required, and no sign detection or recognition are needed.

Another related navigation method in indoor environments is proposed by Aly and Bouguet[2] as part of the Google street view service, which uses six photos captured by professionals to construct an omnidirectional image of each viewpoint inside a room, and then estimates the camera pose and moving parameters between successive viewpoints. Since their inputs are unordered images, they construct minimal spanning tree among complete graph of every viewpoint to select triples for parameter estimations. In our method, since we use sequential video frames, we do not need to find such spatial relationships between images, and thus we can skip these procedures. Therefore we reduce the computation cost and pursue a real-time solution.

Representing and compressing omnidirectional images into compact rotational invariant features was investigated by Zhu et al[17], which uses the Fourier transform of the radial principle components of each omnidirectional image to represent the image. In our paper, based on the observation that an indoor environment usually includes a great number of vertical lines, we explore the omnidirectional features of these vertical lines in both the HSI space and the HSI gradient (G-HSI) space of an omnidirectional image, instead of using original RGB space only in [17], and generate one-dimensional omnidirectional HSI and G-HSI projections (profiles). Then we use the Fourier transform components



(a) (b)

Fig. 3: Smart phone GUI and omnidirectional lens

of these projections as the representation of omnidirectional image to reduce feature size and obtain rotation-invariant features and then find both the viewer's location and heading direction.

3 Overview of Our Approach

The hardware of the system is designed with two components: the smart phone front end part and the server part. The system diagram is shown in Fig. 2. The front end part consists of a smart phone and an omnidirectional lens, which mounts on the phone with a case. In our implementation, we use an iPhone and a GoPano lens, which is shown in Fig. 3.

The software of the system includes two stages: the modeling stage and the query stage. In the modeling stage, the developer of the database (the model) carries the mobile phone and moves along the corridors, covering and recording the video into a database. Geo-tags(e.g. physical location of current frame) are manually labeled. The indexing and localization of a new image frame is related to a frame in the database. To reduce the storage need, we do some preprocessing to the data, which will be discussed in Section 4. In the second stage, a visually impaired user can walk into the area covered in the above modeling stage and take a short video clip. The smart phone extracts video features and sends them to the server via wireless connections. The server receives the query and search the image candidates in the database, and returns the localization and orientation information to the user.

Using all the pixels in images of even a short video clip to represent a scene is too expensive for both communication and computation, and the data are also not invariant to environment variables such as illumination, user heading orientation, and other environment factors. Therefore, we propose a concise and effective

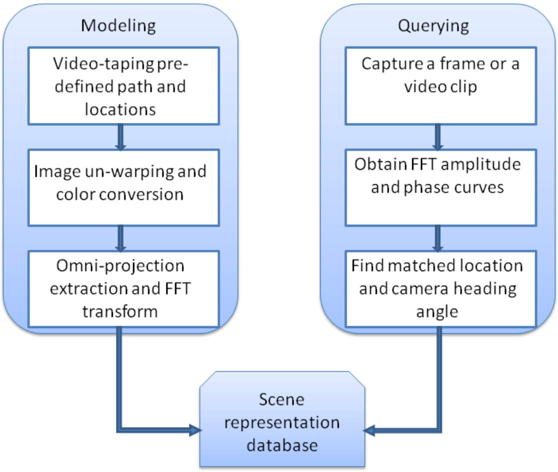


Fig. 4: Work flow of modeling and querying stages

representation for the omnidirectional images by using a number of robust one-dimensional omnidirectional projections (omni-projections) for each panoramic scene. We have observed that an indoor environment often has plenty of vertical lines (door edges, pillar edges, notice boards, windows, etc.), and features along vertical lines can be embedded inside of the proposed omni-projection representations, so these features can be extracted and be used to estimate viewer's locations. Also new extracted features of an input image are used as query keys to localize and navigate in the environment represented by the database.

Because different scenes may have similar omni-projection features, using a single frame may cause false indexing results. We adopt a multiple frame querying mechanism by extracting a sequence of omni-projection features from a short video clip, which can greatly reduce the probability of false indexing. When database scales up for a large scene, it is very time consuming to sequentially match the input frame features with all the images in the database of the large scene. So we use GPGPU to parallelize the query procedure and accelerate the querying speed.

3.1 System diagram

While the system server is running, a user can send a query with new captured video frames, and the corresponding location is searched in the database. Since frames in the database are tagged with geo-location information, the system can provide the location information to the user. Currently, only physical locations relative to the floor plan are tagged, however in the future more information can be added, such as doorplate, offices' name, locations of daily-used facilities(e.g. telephones) etc.

We build a scenes database with the method offline before the users use the system. We call the process of building database as modeling stage, and the process of using database in real time as querying stage.

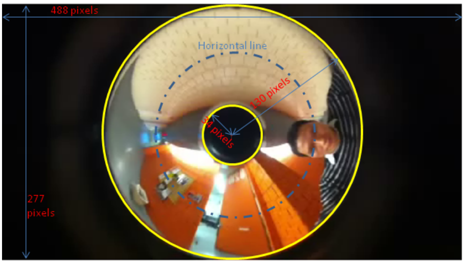
In the modeling stage, we first traverse all the desired paths and locations in an indoor environment and capture the original panoramic video of the scene. Then we perform un-warping to obtain the cylindrical representations of the omnidirectional images, convert the images to HSI color space and carry out a number of other preprocessing operations (such as gradient operations). After that, we project the images' columns to obtain the omni-projection curves for each frame (for both H, S, I and gradients of them). All the curves are normalized. Finally we do the FFT transform to the curves and store the main components of the FFT amplitude curves and phase curves in the database.

In the querying stage, we first obtain normalized projection curves to the frames. Then we again carry out FFT transform to the curves and compute their FFT amplitude and phase curves. Using the amplitude curves, which are rotation-invariant, we search the frames in the database and find the closest matching frames. Using the phase curves of the omni-directional images, we can also estimate the relative rotation angle between a new frame and the matched frame in the database. The work flow of the modeling and querying stages in our system is shown in Fig. 4.

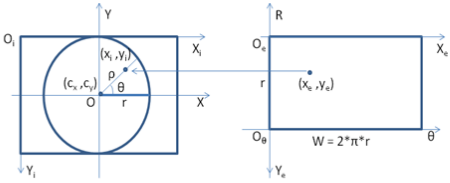
3.2 Cloud and parallel processing

Both the modeling procedure and querying procedure could be very time consuming, so they will be executed in the cloud server part, where parallel processing can be applied to accelerate the procedures. The basic idea of multi-frames indexing is to use a sequence of new captured video frames to query pre-built video frame database to increase the success rate. In our system, we do not directly compare the pixel values of the frames; instead, we extract rotational invariant features from the FFT of HSI or HSI gradient curves, which are obtained by projecting the region of interest of the image frame. Even with this preprocessing step to reduce the size of the input data, the computational cost of multi-frame query in the database would be high if the database is large.

One strategy is to partition input video into individual frames and query the database with each frame. For every input query frame, a straightforward approach is to compare each frame with all the frames one-by-one. Then after all the queries return their matching candidates, which for example, top 5 matches for each frame, an aggregation step of the most consistent sequence of matches can be obtained by considering that both the input and the matched sequences are temporal sequences. In this way the querying process could have three levels of parallelisms. First, instead of comparing input frames sequentially to the database, these frames are independent of each other, we can process them in parallel. Second, for every comparison, we can use multiple threads to compare each input frame with multiple database frames simultaneously, rather than comparing with them one-by-one. Third, some of the operations in obtaining rotation-invariant projection curves, such as the Fourier transform algorithm



(a)



(b)

(c)

Fig. 5: (a) Original video frame and its parameters; (b) geometry relationship between the original and un-warped images; and (c) un-warped omnidirectional image

can take advantage of the parallel processing. For doing this, the original omni-projection curves will be sent from the front end to the server, which is still efficient in communication due to their low dimensionality.

Parallel acceleration is necessary in the query procedure. Without parallel speed up, the time consumed in one single query operation take hundreds of milliseconds on our current experimental database (with several thousand frames), and it would be multiplied if the scale increases. After using parallel acceleration, this time is reduced to several milliseconds and greatly improves the performance of the query response. Details will be provided in Section 5.

4 Calibration and Preprocessing

The original frames captured by the GoPano lens and smart phone camera is a fish-eye-like distorted image, which is shown in Fig. 5(a), and has to be rectified. Fig. 5(c) shows the un-warped image in a cylindrical projection representation, which has planar perspective projection in the vertical direction and spherical projection in the horizontal direction. For achieving this, a calibration procedure is needed to obtain all the required camera parameters.

Assuming that the camera is held up-right and the lens's optical axis is horizontal, the relationship between the original image and un-warped image can be illustrated in Fig. 5(b)[16][15].

Define the original pixel coordinate system as $X_iO_iY_i$, the un-warped image coordinate system is $X_eO_eY_e$, and the original circular image center is (C_x, C_y). Then a pixel (x_e, y_e) in the un-warped image and corresponding pixel (x_i, y_i) in the original image has the following relationship.

$$\begin{cases} x_i = (r - y_e)cos(x_e * \frac{2\pi}{W}) + C_x \\ y_i = (r - y_e)sin(x_e * \frac{2\pi}{W}) + C_y \end{cases} \tag{1}$$

This un-warping process is applied to every frame in the database and all the input query frames. Since the un-warped images still have distortion in the vertical direction (radial direction in the original images) due to the nonlinearity of the GoPano lens, we perform an image rectification step using a calibration target with known 3D information to correct the radial direction so that the projection in the vertical direction of the un-warped cylindrical images is a linear perspective projection. By doing this, the effective focal length in the vertical direction is also found. From this point on, we assume the image coordinates (u, v) are rectified, and the u direction (horizontal direction) represents the 360-degree panoramic view, and the v direction (vertical direction) is perspective.

To represent a scene, six omni-projection curves are extracted from the un-warped images. Three of them are from HSI channels of an original RGB image, and the rest three are from the HSI gradient channels. The gradient of a pixel in an image can be calculated

$$\nabla f(u, v) = \frac{\delta f}{\delta u} du + \frac{\delta f}{\delta v} dv \tag{2}$$

where $\frac{\delta f}{\delta u}$ is gradient in the u direction, and $\frac{\delta f}{\delta v}$ is gradient in the v direction. The magnitude of the pixel gradient is the L-2 norm of the $(\frac{\delta f}{\delta u}, \frac{\delta f}{\delta v})$. In practice, since we mainly focus on the vertical lines in the images as our features, we only use the horizontal gradient. A linear normalization is applied to all the curves here to make sure that curves are at the same scale.

Suppose a cylindrical image is $I(u, v)$, the curve $c(u)$ generated by projecting the ROI can be formalized as following:

$$c(u_t) = \sum_{i=1/2*H-T}^{1/2*H+T} I(u_t, i), t = 0, 1, 2, ..., W - 1 \tag{3}$$

where W and H are image width and height, T is half projection height, and $I(u_t, i), t = 0, 1, 2, ..., W-1$ are the horizontal directions (from 0 to 360 degrees). Therefore the curve $c(u) = c(u_t)$ is an omnidirectional projection curve (or omni-projection curve). With all the six curves, we can store each and every of them into the database, and use them to compare with the new input curves to find the optimal location for the new input frame.

5 Localization by Indexing

Localization is essential to visually-impaired people, since not only it provides the position and orientation of the user, but also it can supply additional information of the environment, e.g. locations of doors, positions of doorplates, etc. When the database scale increases, using key features to do the indexing is necessary in order to obtain real-time performance without losing too much index accuracy. Meanwhile, sequential search is not practical when database scales is up significantly, therefore parallel searching is explored in this paper.

5.1 Overall indexing approach

We use the major components of FFT transform of a number of feature curves as the keys to do the indexing in this paper. Define an omni-projection curve as $c(u), u = 0, 1, 2, ..., W-1$, where W is the curve length in pixel. If the camera rotates around the vertical axis, it will cause a circular shift of the cylindrical representation of the omnidirectional image, which then corresponds to a circular shift to the signal $c(u)$. If an omnidirectional image has a circular shift of u_0 to the right, this is equivalent to rotating the camera coordinate around z axes for $\Phi = -2\pi u_0/N$[17]. Suppose the signal after a right circular shift u_0 is $c'(u)$, we have the following equation:

$$c'(u) = c(u - u_0) \tag{4}$$

Suppose the DFT of $c(u)$ is defined as a_k, the DFT of $c'(u)$ is defined as b_k, then

$$\begin{cases} a_k = \sum_{u=0}^{W-1} x(u)e^{-je2\pi ku/W}, u = 0, 1, ..., W-1 \\ b_k = a_k e^{-je2\pi ku_0/W}, u = 0, 1, ..., W-1 \end{cases} \tag{5}$$

To find the optimal rotation angle (i.e. amount of the circular shift), the problem is equivalent to finding the maximal value of the circle correlation function(CCF).

$$CCF(u_0) \sum_{u=0}^{W-1} c(n) * c(u - u_0) \tag{6}$$

where $u_0 = 0, 1, ..., W-1$.

According to the correlation theorem, we can calculate $CCF(u_0)$ as

$$CCF(u_0) = F^{-1}\{a^*(k)b(k)\} \tag{7}$$

We only carry out this task after the optimal match is found, since it is meaningless to find the shifted angle if the location is not matched correctly. By using the principle components of original feature's FFT transform, we can control the data amount sent to the server and reduce the amount of memory needed to store database in the server too. Real data experiment is shown in the following section.

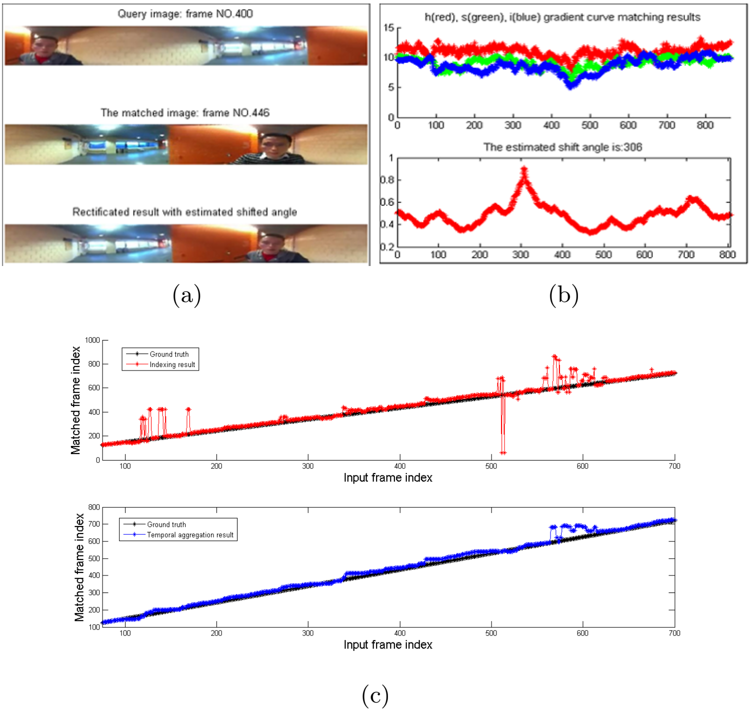
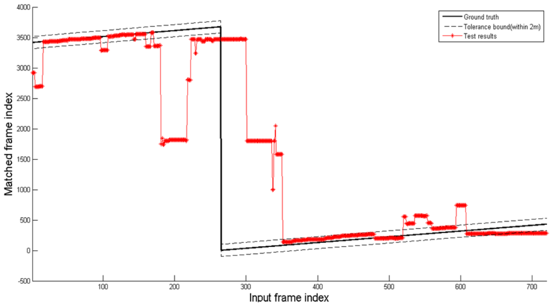


Fig. 6: (a) An example of a query image and its matched result in a database; (b) the matching scores with database frames and the estimated heading differences between the query and database frames; (c) overall matching results of all the test database frames without and with temporal aggregation

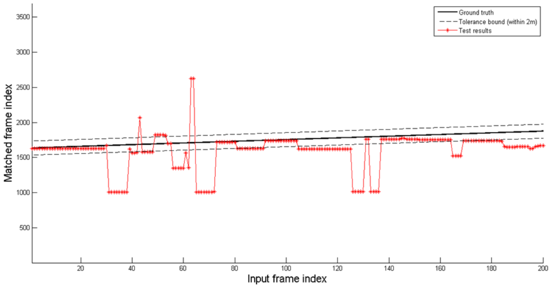
5.2 Real data experiment

In the first experiment, one example of indexing a new query frame on a 862 frames database has been shown in Fig. 6, (a) and (b). Fig. 6(a) shows the input frame, the target frame, and the shifted version of the input image after finding the heading angle difference. In Fig. 6(b), the first plot shows the searching results of the input frame with all the frames in the database using hue (red), saturation (green) and intensity (blue). We found that the information of intensity feature performs the best. The correlation curve is shown on the bottom right, showing that the heading angle difference can be found after obtaining the correct match.

Because of different scenes may have very similar omni-projection curve features, query with only one single frame may cause false matches, as shown in Fig. 6(c)'s top curve. In this figure, the horizontal axis is the index of input frames (of a new sequence) and the vertical axis is the index of database frames (of the old sequence). Both sequences cover the same area. The black curve shows the ground truth matching result, and the red curve on the top curve



(a)



(b)

(c)

Fig. 7: (a) Matching results near the starting point of the loop; (b) matching results in the middle of the loop; (c) a pair of mismatching results

shows the matched results by our system. There are a few mismatches around frame 150, 500, and 600 due to the scene similarities. This leads us to design a multiple-frame approach: if we use a short sequence of input frames instead of just one single frame to perform the query, a consistent match results for all the input frames will yield a much more robust result. Another situation where the feature we selected is prone to fail is when either the camera used to capture training data or testing data has large non-perpendicularity in position. This can be solved by offering the users proper training as well as further algorithm optimization in the future. Fig. 6(c)'s below curve shows the testing results with temporal aggregation, where for every frame, its nearby 25 frames' querying results are aggregated and the median index value is used as the final result. As we can see from the curve, temporal aggregation can reduce the mismatching rate and generate more robust results.

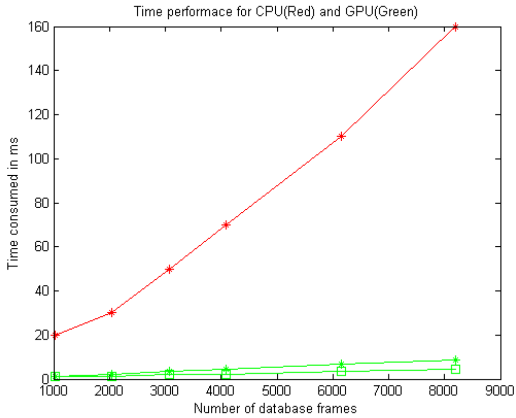


Fig. 8: Time usage with and without GPU acceleration: Red without GPU; Green with GPUs. Curves with squares are experiments using 1024 threads while curves with asterisks are experiments using 2048 threads

In the second experiment,the entire floor of a building is modeled, as shown in Fig. 1. We first capture a video sequence of the entire floor as the training database, whose path is shown as the red line. We then capture two other short databases(along the dark blue line and the light blue line) as the testing databases. Some sample omnidirectional images used in the modeling process are shown around the map in Fig. 1, and their geo-locations are attached to the floor map too. Fig. 7 shows matching results using the two test databases against the large scale database. Fig. 7(a) shows the results using the frames near the starting and ending position. Starting point and ending point are pointed out for visualization purpose. Fig. 7(b) shows the results using frames in the middle of the loop. The black line is the ground truth, and the dashed black line is the tolerance bound with the accuracy within 2 meters. Because it is inevitable to avoid scene similarity, there are some mis-matching results. For example, in Fig. 7(c), the first image is the best matched result and the second one is the original query image, however they are images of two totally different locations.

If using only a single CPU to search sequentially, the amount of time consumed would increase proportional to the number of frames in the database. Therefore we use GPUs to do the query in parallel, so that we can search all the frames and compare an input frame to multiple database frames at the same time, which will greatly reduce the time used. Fig. 8 shows the time used with and without many-core GPUs for a database with the number of images changed from 1000 frames to 8000 frames. In the single CPU version, the time spent increases from 20 ms to 160 ms, whereas using a many-core GPU (Kepler K20 chip), the time is significantly reduced (from 1.13 ms to 8.82 ms). Note that the current test only has a database with a few thousand frames. With a larger database of an indoor scene, the time spending on a single CPU will be prohibitive, whereas using multi-core CPUs/GPUs, the time spending can be greatly reduced. Instead, since we can apply tens of thousands of threads in one or multiple GPUs, the acceleration rate has potential to improve.

6 Conclusion and Discussion

In this paper we have proposed a mobile panoramic system to help the visually impaired people to localize and navigation in indoor environments. We use a smart phone with panoramic camera and high performance server architecture to ensure the portability and mobility of the user part and take advantage of the huge storage as well as high computation power of the server part. An image indexing mechanism is used to find the rough location of an input image (or a short sequences of images), and a pose and moving direction estimation algorithm is applied to refine the localization result and guide the user to a desired location. To improve the query speed and ensure a real time performance, we use multi-core GPUs to parallelize the query procedure. The experiment results on current database shows that the system can achieve both accurate and fast query performance.

There are a few issues we will be dealing with in the future. First, a large scale scene database, for example, multiple floors of an entire building, or a number of buildings on campus, will be build and used to create more testing environments. Second, hierarchical and context-based methods can be used to avoiding searching the entire database for every query. For example we can use GPS or WiFi to obtain rough location information and localize the user in the nearby places before we search the database around those locations. Third, user interface in communicating the localization and navigation information to a blind user, as well as implementation of the front end algorithms on the mobile phone should be optimized to make it more natural for the user to use.

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