IN-CAR TOUR GUIDANCE IN OUTDOOR PARKS USING AUGMENTED REALITY AND OMNI-VISION TECHNIQUES WITH AN AUTOMATIC LEARNING CAPABILITY*

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ABSTRACT

A new augmented reality (AR)-based tour guidance system with an automatic learning capability for use in a vehicle driven in an outdoor park area is proposed. With a common map of the park area, a user can easily construct a tour guidance map for the system by an environment learning method. Accordingly, the system provides tour guidance information to in-car passengers using the constructed map in an AR manner. To construct the tour guidance map, the information of tour paths and along-path buildings are acquired from the common map of the park area. Next, along-path vertical-line features are learned by driving the vehicle along the path once. A method is proposed for this purpose, which detects vertical lines in omni-images according to rotational invariance property of the omni-image. Also, a new analytic technique for 3D space data acquisition based on a space-mapping technique for image-to-world space transformation is proposed. In the navigation phase, the system uses the learned data to locate the vehicle by a method which integrates the GPS data and the omni-images to analyze the vehicle position on the map. Moreover, to display AR images to the passenger, a method for generating a passenger-view image from an acquired omni-image and a method for augmenting building information on correct positions in the passenger-view image using the building positions are proposed. Good experimental results showing the feasibility of the proposed system are also included.

Keywords: *omni-image; augmented reality; in-vehicle tour guidance; space mapping; automatic learning; vertical-line feature*

1. INTRODUCTION

In recent years, the augmented reality (AR) technique becomes more and more popular for uses in many application domains. With the AR techniques, it becomes feasible to develop an automatic in-car tour guidance system for use in outdoor park areas. Moreover, with the popularity of mobile devices nowadays, it is desired to allow an in-vehicle passenger to obtain tour guidance information by inspecting the screen of a hand-held mobile device while visiting a park area by car riding.

To enhance the convenience of using such a system, it is easy to see that the user (possibly the manager of a park area) needs a simple way to set up the system, including the establishment of a digital guidance map with associated data of the visited park area for use in the process of automatic guidance. Therefore, in this study we investigate this topic of *automatic learning* for such an AR-based guidance system, so that the user can easily construct the guidance map of the park area for tour guidance. This contrasts with the system proposed by Wei, Lin, and Tsai [1] — learning for their system should be conducted *manually*, causing inconvenience to the system designer and the users.

To implement such a type of AR-based guidance system with a learning capability, we affix a *two-camera omni-imaging device* on the top of the vehicle to get the image data of the environment. Also, a method for vehicle localization is necessary. That is, AR techniques will work only if the system knows the position of the environment so that touring information can be augmented at right places on the screen of the mobile device held by an in-vehicle passenger. Although AR techniques based on the Global Positioning System (GPS) [2] are getting popular nowadays, they are sometimes difficult to use for the purpose of car positioning or they might cause car localization errors because of their imprecision in positioning, with errors ranging from 3 to 15 meters. This might cause unacceptable AR effects on the mobile-device screen — the augmented guidance information will appear at incorrect positions on the screen, especially when the vehicle is driven through narrow roads with buildings close by. Therefore, we propose in this study to integrate the uses of not only the GPS but also vision-based vehicle localization techniques using omni-cameras to implement a more

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accurate and effective tour guidance system for use in park areas.

Various methods for vision-based vehicle navigation by the use of landmarks have been developed in the past decade. Betke and Gurvits [3] proposed a standard localization method by identifying landmarks in the surrounding environment and finding their positions in a map built in advance to localize the vehicle. Li et al. [4] proposed a positioning system using four artificial landmarks and an omni-directional visual sensor. An integration of the AR technique and a video surveillance system is developed in this study. In a similar work, a method for navigation in a real environment using panoramic images was proposed by Grosch [5].

Also AR techniques for outdoor applications have been widely investigated in recent years. In this aspect, Cham et al. [6] proposed a method for estimating the pose of a camera based on features extracted from a single omni-directional image of an urban scene, given a 2D map of building outlines without 3D geometric information and appearance data. Park et al. [7] utilized the vertical edges of buildings for pose computation with the initial values obtained from a GPS and a digital compass using average field-of-view cameras. Narzt et al. [8] proposed an AR navigation system which improves the depiction of virtual objects in a real world to assist drivers.

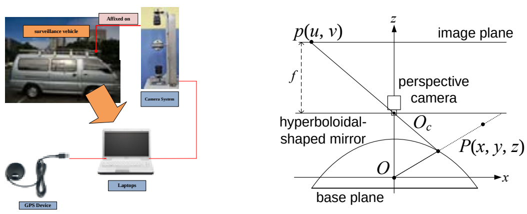
The remainder of this paper is organized as follows. In Sec. 2, the configuration and processes of the proposed system are introduced in detail. In Sec. 3, the idea of the proposed vehicle localization method by the use of vertical-line features is described. In Sec. 4, the proposed method for learning landmarks in the outdoor environment is presented. In Sec. 5, the proposed method for vehicle localization in tours in outdoor park environments is described. In Sec. 6, the proposed method for AR-based tour guidance is presented. In Sec. 7, some experimental results are shown. Finally, conclusions and some suggestions for future works are given in Sec. 8.

2. SYSTEM CONFIGURATION AND PROCESSES

The configuration of the proposed system is shown in Fig. 1(a). An imaging device with two omni-cameras is affixed on the top of the vehicle. The two omni-cameras, each as illustrated in Fig. 1(b), are connected back to back and coaxially. Furthermore, a laptop computer is used in the vehicle to control the imaging device and a GPS dongle, as shown in Fig. 1(a).

Mainly two processes are run on the proposed system, namely, the learning process and the navigation process. In the learning process, a *guidance map* for use in the navigation process is constructed. For that, at first a common digital map of the park area to be visited is fetched, and information of every tour path and along-path buildings is constructed accordingly. Next, the vehicle is driven along every path, and on each selected spot of the path, the system “learns” the vertical-line features observable around, which come mainly from along-path light poles in this study, by the following steps: 1) compute the rough vehicle position in the map by use of the GPS device; 2) detect the vertical-line features in the upper and lower omni-images and combine the two results; 3) use the base point of each detected vertical-line feature to compute its position in the map; 4) use the top point of the detected vertical-line feature to compute its height. The computed data then are kept as part of the learned guidance map.

In the navigation process, with the learned map available, the system conducts the following tasks in every navigation cycle at selected path spots: 1) detect the vertical-line features in the upper omni-image; 2) use each detected vertical-line feature with the known information about it (its position and height, etc.. kept in the guidance map) to locate the vehicle; 3) calculate accordingly the positions of the close-by buildings seen along the path and locate them on the learned guidance map; 4) generate a passenger-view image from the lower omni-image; 5) augment the names and related information of the buildings around on the passenger-view image at correct positions for in-car passengers to inspect to get tour guidance information.



(a) (b)

Fig. 1. Proposed system. (a) Configuration of proposed system. (b) Structure of omni-camera used in the proposed system.

3. IDEA OF PROPOSED VEHICLE LOCALIZATION BY VERTICAL LINES

3.1 Idea of Proposed Vehicle Localization Technique

The core function of the proposed system is *vehicle localization* by which AR-based tour guidance can be accomplished. The main idea of the proposed vehicle localization technique is to use vertical-line features appearing on alone-path landmarks — light poles — to derive the vehicle position by analyzing the geometric relationship between each landmark and the vehicle. This idea is based on two properties of the omni-image acquired by the omni-camera used in the imaging device, which we review here:

1) the *radial-line property*: a vertical line L in the real-world space (perpendicular to the ground) appears to be a radial line l going through the center of the omni-image if the base plane of the mirror of the omni-camera is parallel to the ground; and

2) the *rotational-invariance property*: each real-world point P appears to be an image point p in the omni-image with its orientation in the image being identical to that of P with respect to the orientation of the omni-camera as seen from the top.

From the above two properties, it is not difficult to figure out a third property, which we call the *vertical-line property*:

3) the *vertical-line property*: the orientation of the above-mentioned radial line l in the omni-image is identical to that of the *base point* of the corresponding vertical line L in the real world with respect to the orientation of the omni-camera as seen from the top.

Accordingly, as long as a vertical-line landmark is detected by the system, the geometric relationship between the vehicle and the landmark can be computed, which together with the known position of the landmark learned in advance can be used to locate the vehicle in the environment. More details are described next.

3.2 Vehicle Localization by Use of a Vertical Line

After detecting a vertical-line feature l in an omni-image which comes from a landmark L in the real world at the currently-visited spot along the path, we can compute the orientation θ of L simply as that of l according to the above-mentioned vertical-line property. Moreover, according to the "learned" tour guidance map, the position (L_X, L_Y) of L and the line equation $A_SX + B_SY + C_S = 0$ of the currently-visited line segment S of the tour path may be obtained easily as well.

Accordingly, we can derive the 2-D equation of the line E going through the location of the vehicle (actually through the omni-camera centers) and the position of the landmark L in terms of the data, θ, (L_X, L_Y), and (A_S, B_S) to be

$$A_EX + B_EY + C_E = 0$$

where

$$A_E = A_S \times \cos\theta - B_S \times \sin\theta\,;$$
$$B_E = A_S \times \sin\theta + B_S \times \cos\theta\,;$$
$$C_E = -L_X \times A_E - L_Y \times B_E\,. \quad (1)$$

The above equalities for the coefficients A_E, B_E, and C_E are derived in the following way. At first, notice that (A_E, B_E) and (A_S, B_S) are the normal vectors of lines E and S, respectively. Moreover, as illustrated in Fig. 2(c), the angle between E and S is θ, which by definition is also the rotation-angle difference between their normal vectors, (A_E, B_E) and (A_S, B_S). Hence, the pair (A_E, B_E) is just the values resulting from multiplying (A_S, B_S) by the following rotation matrix

$$\begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix},$$

leading to the first two equations in (1). As to the third in (1), we can derive it by substituting the known coordinate values (L_X, L_Y) and the derived coefficient values (A_E, B_E) into the equation $A_EX + B_EY + C_E = 0$ to get C_E.

Knowing that the vehicle is located at the intersection of the lines E and S as illustrated in Fig. 2, we can compute the vehicle position (V_X, V_Y) from the equations of E and S, $A_EX + B_EY + C_E = 0$ and $A_SX + B_SY + C_S = 0$, leading to the following equations:

$$V_X = \frac{C_S \times B_E - C_E \times B_S}{A_S \times B_E - A_E \times B_S}\,;$$
$$V_Y = \frac{A_S \times C_E - A_E \times C_S}{A_S \times B_E - A_E \times B_S}\,. \quad (2)$$

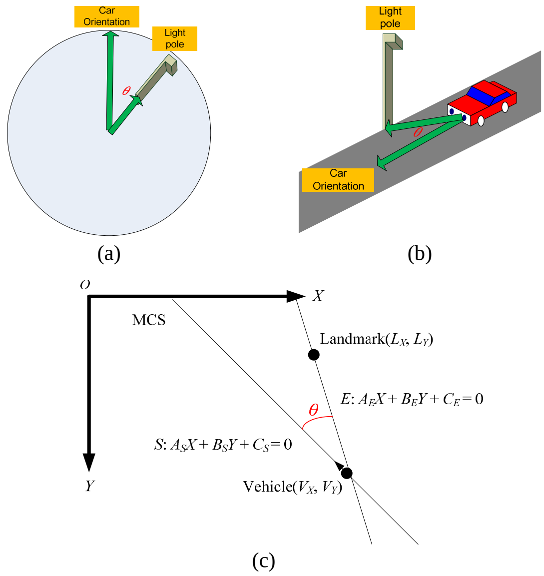


Fig. 2. An illustration of proposed vehicle localization. (a) An omni-image with a detected light pole. (b) An illustration of the relationship between the vehicle and the light pole in the real world. (c) A top-view illustration of the relationship between the vehicle and the light pole.

4. AUTOMATIC LANDMARK LEARNING BY GPS AND SPACE MAPPING

4.1 Idea of Proposed Landmark Learning Technique

With the above-described idea of the proposed vehicle localization method, all the landmarks along the tour path must be learned in advance. In this study, we propose a method to conduct this work *automatically* by driving the vehicle alone the path *once*. In the driving process, at first the system detects vertical-line features of the landmarks at each selected spot along the tour path according to the previously-mentioned vertical-line property of the omni-image. Then, using the space-mapping technique proposed by Jeng and Tsai [9], an image point can be mapped into a real-world point. Hence, with the base point of a vertical line in the omni-image being detected, the relative position of the vertical line with respect to the vehicle in the real world can be acquired. It is noted that, the vehicle is stopped while doing this work. Therefore, we can take the GPS signal for a multiple of times and compute a more accurate vehicle position in the map by filtering the GPS signal.

With the above-computed information about the vehicle and the landmark, we can locate the landmark in the map. Also, using the detected top point of the vertical line in the omni-image together with its position and the vehicle position, its height can be computed. In this way, all the landmarks alone the path are "learned," yielding their positions and heights as output. More details are described in the following.

4.2 Detection of Vertical Lines in Omni-images

At each spot of the path selected for learning, the system gets two omni-images captured by the upper and lower cameras of the omni-imaging device, respectively, like the example shown in Figs. 9(b) and (c). Then, they are transformed into YUV images with the Y values composed as two gray-level images, from which the canny edge detector is applied to extract edge points. Furthermore, based on the vertical-line property in omni-images mentioned previously and starting from the center of the omni-image, unbroken radial lines are found out as desired vertical lines by searching lines of all radial directions like scanning a radar and detecting those ones with a certain width and without large gaps. Finally, we combine the two results from the two omni-images (upper and lower) to eliminate redundant data, and get the base and top points of each landmark in the lower and upper omni-images, respectively.

4.3 Localization of Landmarks

In this study, we propose a technique to locate a real-world object, like the landmark of light pole, by the use of just one omni-image. At first, the space-mapping method proposed by Jeng and Tsai [9] is adopted to construct a so-called pano-mapping table to map each real-world light ray into an omni-image point. The method is reviewed here. Specifically, in the pano-mapping table, each entry E with an azimuth-elevation angle pair (θ, ρ) is mapped to a pixel p with coordinates (u, v) in the input omni-image I as shown in Table 1.

Table 1. An example of pano-mapping table of size M×N.

	θ_1	θ_2	θ_3	θ_4	…	θ_M
ρ_1	(u_{11}, v_{11})	(u_{21}, v_{21})	(u_{31}, v_{31})	(u_{41}, v_{41})	…	(u_{M1}, v_{M1})
ρ_2	(u_{12}, v_{12})	(u_{22}, v_{22})	(u_{32}, v_{32})	(u_{42}, v_{42})	…	(u_{M2}, v_{M2})
ρ_3	(u_{13}, v_{13})	(u_{23}, v_{23})	(u_{33}, v_{33})	(u_{43}, v_{43})	…	(u_{M3}, v_{M3})
ρ_4	(u_{14}, v_{14})	(u_{24}, v_{24})	(u_{34}, v_{34})	(u_{44}, v_{44})	…	(u_{M4}, v_{M4})
…	…	…	…	…	…	…
ρ_N	(u_{1N}, v_{1N})	(u_{2N}, v_{2N})	(u_{3N}, v_{3N})	(u_{4N}, v_{4N})	…	(u_{MN}, v_{MN})

According to the mirror-surface geometry shown in Fig. 1(b) which we assume as usual to be radially symmetric, a relationship, called the *radial stretching function* and denoted as f_s, between the elevation angle ρ and the radial distance r of a point p in the image plane with respect to the image center may be established, according to Jeng and Tsai [9], to be:

$$r = f_s(\rho) = a_0 + a_1 \times \rho + a_2 \times \rho^2 + \ldots + a_5 \times \rho^5$$

where the coefficients a_0 through a_5 are computed in the following way using the known image coordinates (u_k, v_k) and the corresponding known world coordinates (X_k, Y_k, Z_k) of six real-world landmark points P_1~P_6 selected manually in advance:

(1) compute the radial distances r_k for each of the six points using the following equation:

$$r_k = \sqrt{u_k^{\,2} + v_k^{\,2}}\,; \tag{2}$$

(2) compute the elevation angle ρ_k for each of the six points using the following equation:

$$\rho_k = \tan^{-1}\left(\frac{Z_k}{\sqrt{X_k^{\,2} + Y_k^{\,2}}}\right); \tag{3}$$

(3) solve the following six simultaneous equations to get the values of a_0 through a_5 where k = 1~6:

$$r_k = f_s(\rho_k) = a_0 + a_1 \times \rho_k + a_2 \times \rho_k^{\,2} + \ldots + a_5 \times \rho_k^{\,5}. \tag{4}$$

With a_0 through a_5 derived above, the pano-mapping table like that of Table 1 is constructed in the following way: for each real-world point P_{ij} with azimuth-elevation angle pair (θ_i, ρ_j), compute the coordinates (u_{ij}, v_{ij}) of the corresponding image pixel p_{ij} by the following equation:

$$u_{ij} = f_s(\rho_j) \times \cos\theta_i\,;\ \ v_{ij} = f_s(\rho_j) \times \sin\theta_i\,. \tag{5}$$

After the table is constructed, when an image pixel p with coordinates (u, v) in a given omni-image is given and checked by table lookup to be located in entry E_{ij} with coordinates (u_{ij}, v_{ij}) in Table 1, the azimuth-elevation angle pair of the corresponding real-world point P can be obtained to be (θ_i, ρ_j) and a light ray passing through the mirror center and the real-world point can be derived, as shown in Fig. 3.

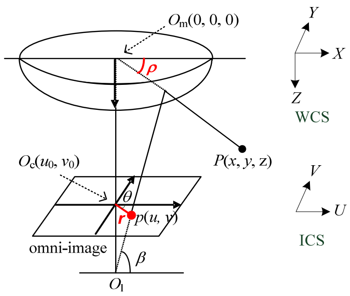


Fig. 3 Relationship between a real-world point and an omni-image point.

Accordingly, given a real-world point P on an object with a fixed known height value h (e.g., the ground, the base of a building, the base of a light pole, etc.), we can compute the 3-D world coordinates (X, Y, Z) of P in a way as illustrated in Fig. 4 by the following equations:

$$X = \frac{h}{\sin\rho} \times \cos\rho \times \cos\theta,$$

$$Y = \frac{h}{\sin\rho} \times \cos\rho \times \sin\theta,$$

$$Z = h \tag{6}$$

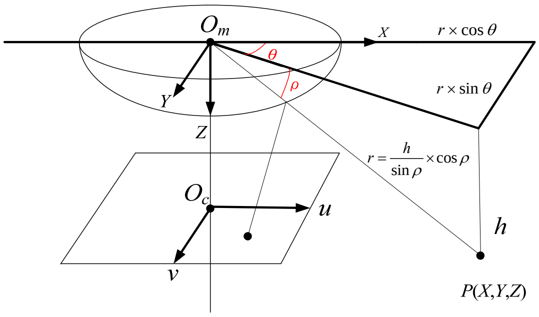


Fig. 4 An illustration of localization of a real-world point P.

Hence, to locate a landmark L in the real world, we can take the coordinates in the image of the detected base point (u_b, v_b) of a vertical-line feature of L as well as the fixed Z-axis distance of the base point of L in the real world from the focal point of the lower mirror as input parameters, and apply the method described above using Equations (6) to localize landmark L.

Next, the map coordinates of the vehicle location on the currently-visited spot of the tour path is computed by taking the GPS signal multiple times and computing the average of the coordinate values of the multiple signals. Also, the direction of the vehicle in the map can be represented by the orientation of the currently-visited line segment of the tour path.

Finally, with the data of 1) the vehicle position (V_x, V_y) in the map; 2) the landmark position (X, Y, Z) in the real world; and 3) the orientation angle θ of the vehicle as input, we can locate the landmark on the guidance map by mapping (X, Y, Z) into the corresponding map coordinates (M_x, M_y) by the following equations according to the geometry shown in Fig. 5:

$$M_x = V_x + X\sin\theta - Y\cos\theta,$$
$$M_y = V_y + X\cos\theta - Y\sin\theta, \qquad (7)$$

where ICS in Fig. 5 means the image coordinate system and MCS means the map coordinate system.

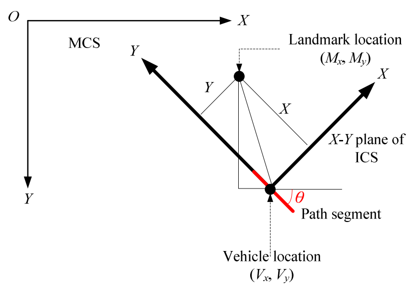


Fig. 5 An illustration of locating a light pole in the map coordinate system.

4.4 Calculation of Heights of Landmarks

As described above, we now have the positions of the vehicle and the landmark on the map as described by Equations (2) and (7). Hence, we can derive their distance D. Also, the elevation angle ρ of the top point of the landmark in the real world with respect to the focal point of the mirror of the upper camera can be acquired by taking the top point (u_t, v_t) of the upper omni-image as input to look up the pano-mapping table. Then, we can use the data of 1) the elevation angle ρ of the top point; 2) the height h of the focal point of the upper mirror; and 3) the distance D between the vehicle and the landmark as input to calculate the height H of the landmark by the following equation according to the geometry shown in Fig. 6:

$$H = h + D \times \tan\rho\,. \qquad (8)$$

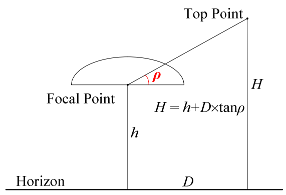


Fig. 6 An illustration of calculating the height of a light pole.

5. VEHICLE LOCALIZATION BY INTEGRAL USE OF OMNI-IMAGING DEVICE AND GPS DEVICE

In the navigation stage of the system, as the vehicle moves on, the system conducts the localization work in every navigation cycle until reaching the pre-selected end of the tour path. In each cycle, the system acquires an upper omni-image and takes the GPS signal once as the parameters of the environment which corresponds to the currently-visited spot. In the following, we introduce the details of the vehicle localization process conducted by the system in each cycle.

Firstly, the system computes the map coordinate values $v(v_x, v_y)$ from the GPS signal, which are maintained in the system as a part of the system state. It represents a rough position of the vehicle because of the inaccuracy of the GPS as discussed before. Hence, we set accordingly a distance range with a fixed value on the path as shown in Fig. 7, which includes all the possible positions of the vehicle in this cycle. Then, using the coordinate values $v(v_x, v_y)$, we choose a nearest L in the tour guidance map as the target to be detected. With the learned data of landmark L including its position (L_X, L_Y) and height H, we can improve the light pole detection process using the following two schemes.

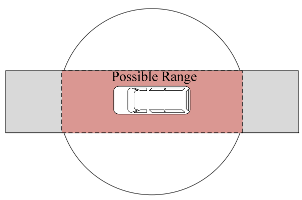


Fig. 7 An illustration of the range of the possible vehicle position.

(1) Limiting the angle θ of the detected landmark to be in a range [θ_s, θ_e] —

Assuming that the two end points of the set range of the vehicle position on the path are (v_{x_s}, v_{y_s}) and (v_{x_e}, v_{y_e}), we can compute the angle range [θ_s, θ_e] by the following equations according to the geometry shown in Fig. 8:

$$\sin\theta_s = \frac{L_Y - v_{y\_s}}{\sqrt{(L_X - v_{x\_s})^2 + (L_Y - v_{y\_s})^2}},$$

$$\cos\theta_s = \frac{L_X - v_{x\_s}}{\sqrt{(L_X - v_{x\_s})^2 + (L_Y - v_{y\_s})^2}};$$

$$\sin\theta_e = \frac{L_Y - v_{y\_e}}{\sqrt{(L_X - v_{x\_e})^2 + (L_Y - v_{y\_e})^2}},$$

$$\cos\theta_e = \frac{L_X - v_{e\_s}}{\sqrt{(L_X - v_{e\_s})^2 + (L_Y - v_{e\_s})^2}}. \tag{9}$$

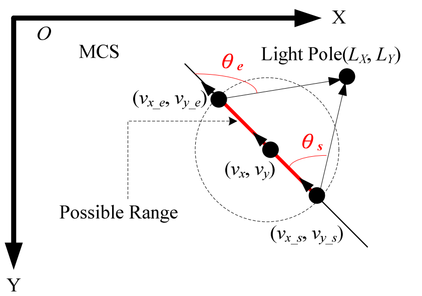


Fig. 8 An illustration of the angle range [θ_s, θ_e].

(2) Limiting of the elevation angle ρ of the top points of the detected light pole to be in an angle range [ρ_s, ρ_e] —

Also, we can compute the angle range [ρ_s, ρ_e] by the following equations according to the geometry shown in Fig. 9:

$$\tan\rho_s = \frac{H - h}{\sqrt{(L_X - v_{x\_s})^2 + (L_Y - v_{y\_s})^2}};$$

$$\tan\rho_e = \frac{H - h}{\sqrt{(L_X - v_{x\_e})^2 + (L_Y - v_{y\_e})^2}}, \tag{10}$$

where h is the known height of the focal point of the mirror of the upper camera.

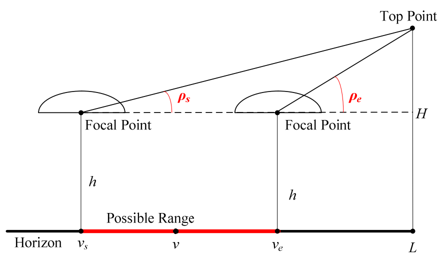


Fig. 9 An illustration of computing the angle range [ρ_s, ρ_e].

With the above two limitations set, the system now can use the method described in Sec. 4.2 to detect the landmark — a light pole, and then calculate the position of the vehicle by the method described in Sec. 3.

However, sometimes the landmark detection process could fail due to noise in the environment. As a countermeasure, we calculate the position of the vehicle (V_X, V_Y) in this situation by the following two equations:

$$V_X = V_{X\_last} + (v_x - v_{x\_last});$$
$$V_Y = V_{Y\_last} + (v_y - v_{y\_last}), \tag{11}$$

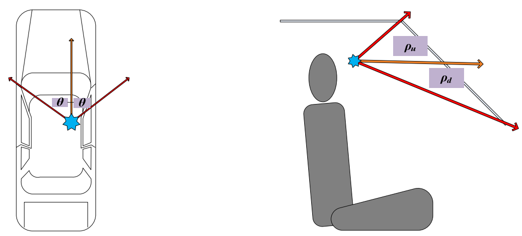
where (V_{X_last}, V_{Y_last}) are the coordinates of the vehicle position computed by the proposed method, and (v_{x_last}, v_{y_last}) are the coordinates of the vehicle position computed from the GPS signal as mentioned above, in the *last* navigation cycle.

6. PROPOSED AR-BASED TOUR GUIDANCE

6.1 Construction of Passenger-view Images from Omni-images

In this study, we use the passenger-view image as the base for generating the desired AR image for the in-vehicle passenger to inspect. The passenger-view image is what the passenger sitting aside the driver sees through the vehicle window. A method for generating this passenger-view image from the acquired omni-image is proposed in this study. The method is based on the uses of a space-mapping method proposed by Jeng and Tsai [9] and some geometric information about the interior space structure of the vehicle.

Firstly, we assume that the viewpoint originates from the right-side passenger seat as the blue star shown in Fig. 10, and the field of view (FOV) is set to be θ for the left or right side as shown in Fig. 10(a), and ρ_u and ρ_d for the upper and lower sides, respectively, as shown in Fig. 10(b). Next, we use the method of Jeng and Tsai [9] to transform the acquired omni-image to be a perspective-view image as illustrated by Figs. 11(a) and (b). Then, by shifting the viewpoint position from the center of the imaging-device to the blue-star position as illustrated in Fig. 10 and cutting out the part of the perspective-view image which are confined by the four FOV's θ, θ, ρ_u, and ρ_d, we can get the desired passenger-view image, as illustrated in Fig. 11(c).



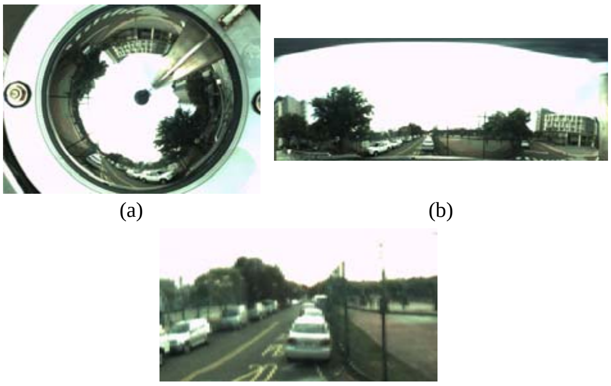
(a) (b)

Fig. 10. Illustration of shifting the viewpoint. (a) Top-view of vehicle where blue star is the passenger's viewpoint and the green star is the camera's viewpoint. (b) Side-view of the vehicle.

6.2 Augmenting Building Names on Images

After localizing the vehicle, we can obtain the positions of the buildings observable by the passenger according to the environment map. Then, we can project the building positions onto the passenger-view image, on which we can finally *augment* the learned information, such as the name, of each building to obtain the desired AR image for displaying on the mobile device.

More specifically, when the middle part of the building is in the passenger-view image, we augment the building name right on it. And when only part of the building can be seen in the image, we augment the building name on the boundary of the image where the partial building shape appears.



(a) (b) (c)

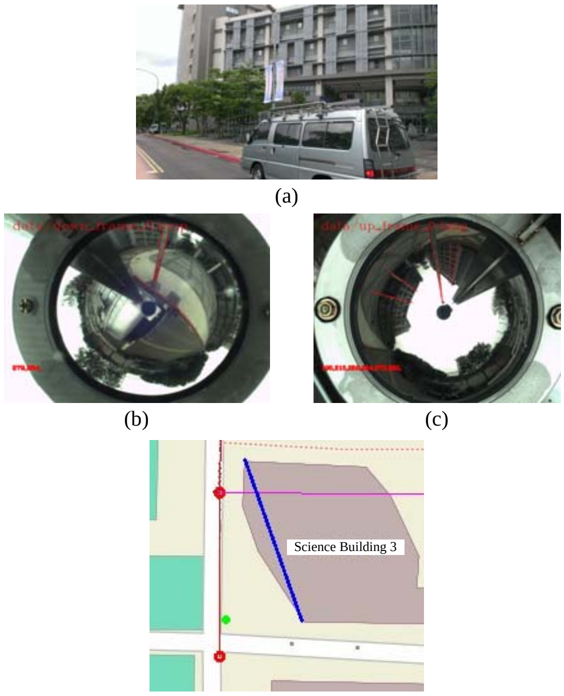
Figure 11. Illustration of creating a passenger-view image. (a) Omni-image acquired with the omni-camera. (b) Perspective-view image generated from (a). (c) Passenger-view image obtained from (b).

7. EXPERIMENTAL RESULTS

In this section, we show some experimental results of applying the proposed AR-based guidance system for touring a park area on a vehicle. Firstly, we construct a map of the park area which includes the information of the tour paths and the buildings as shown by the example of Fig. 12.

Fig. 12. The constructed environment map.

In the learning stage, we drove a vehicle as shown in Fig. 13(a) on a path shown in Fig. 12. As illustrated in Figs. 13(b) and (c), the vertical-line feature of an along-path landmark like the one shown in Fig. 13(a) in each acquired omni-image is detected, and the result is added to the map as a green point as shown in Fig. 13(d). Finally, with all the learned landmarks marked in the environment map, construction of a tour guidance map is completed.



(a) (b) (c) (d)

Fig. 13. A result of learning. (a) An image of the vehicle driven on the path. (b) The result of vertical-line feature detection in the lower omni-image. (c) The result of vertical-line feature detection in the upper omni-image. (d) The result of learning a landmark.

After the learning process, the system uses the learned data to provide AR-based guidance to the user. During the tour, the system locates the vehicle in every navigation cycle on the tour guidance map by the proposed method described in Sec. 5 using the upper omni-images and the GPS device. As can be seen from the experimental results shown in Figs. 14(c) and (d), the system detected the learned landmark features in the upper omni-images at different times in the tour, and computed the positions of the vehicle according to the detection results to locate it on the tour guidance map as shown by the yellow points in Figs. 14(e) and (f).

After locating the vehicle, the system used the result to generate an AR image on the user-held mobile device. Fig. 15 shows two examples of such results. In the first example, an image of the vehicle on a spot along the path is shown in Fig. 15(a), an omni-image taken while the vehicle passed the spot is shown in Fig. 15(b), and the generated passenger-view image with the nearby building name augmented is shown in Fig. 15(c). Another example is shown in Figs. 15(d) through (f).

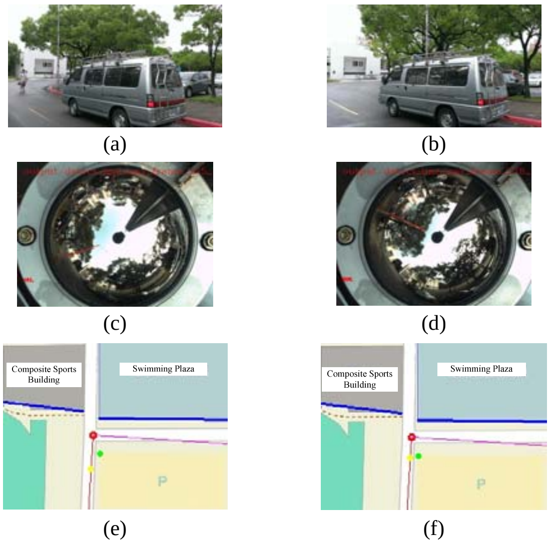


Fig. 14. Two results of landmark detection and vehicle localization. (a) An image of the vehicle driven on a path. (b) Another image of the vehicle driven on the path. (c) A result of landmark detection at the spot of (a). (d) Another result of landmark detection at the spot of (b). (e) Vehicle location result (indicated by a yellow point) using (c). (f) Vehicle location result (indicated by a yellow point) using (d).

8. CONCLUSIONS

An AR-based tour guidance system with an automatic learning capability for uses in outdoor park areas using a two-camera omni-imaging device and a GPS device has been proposed. To design such a system, several techniques have been proposed, including: 1) a method for generating the environment map of the outdoor park area; 2) a method for automatic learning of the vertical-line features in the park area; 3) a method for locating the vehicle along a tour path by integration of the data provided by the omni-imaging device and the GPS device; 4) a method for generating passenger-view images; and 5) a method for AR-based tour guidance in the park area. The experimental results have revealed the feasibility of the proposed system.

In the future, more studies may be directed to developing the capability of detecting features of different shapes to adapt the proposed system to more diversified environments; as well as to extension of the system functions for use in more complicated tour areas.

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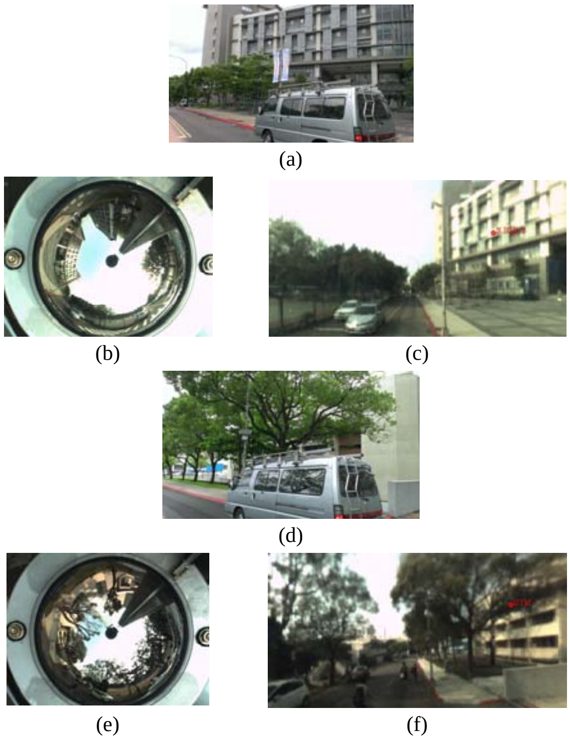

Fig. 15. AR-based navigation. (a) An image of the vehicle on a path spot. (b) An omni-image acquired. (c) Passenger-view image generated from (b) with the name of nearby the building augmented. (d) Another image of the vehicle on another path spot. (e) Another omni-image acquired. (f) Passenger-view image generated from (e) with the name of the nearby building augmented.

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