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Dynamic Omnidirectional Vision Localization Using a Beacon Tracker Based on Particle Filter

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1. Introduction

Autonomous navigation is of primary importance in applications involving the usage of Autonomous Guided Vehicles (AGVs). Vision-based navigation systems provide an interesting option for both indoor and outdoor navigation as they can also be used in environments without an external supporting infrastructure for the navigation, which is unlike GPS, for example. However, the environment has to contain some natural or artificial features that can be observed with the vision system, and these features have to have some relationship to spatial locations in the navigation environment (Cao, 2001). The omni-directional camera system produces a spherical field of view of an environment. This is particularly useful in vision-based navigation systems as all the images, provided by the camera system, contain the same information, independent of the rotation of the robot in the direction of the optical axis of the camera. This makes the computed image features more suitable for localization and navigation purposes (Hrabar & Sukhatme, 2003; Hampton et al., 2004). The methods proposed have been developed for vision-based navigation of Autonomous Ground Vehicles which utilize an omni-directional camera system as the vision sensor. The complete vision-based navigation system has also been implemented, including the omni-directional color camera system, image processing algorithms, and the navigation algorithms. The actual navigation system, including the camera system and the algorithms, has been developed. The aim is to provide a robust platform that can be utilized both in indoor and outdoor AGV applications (Cauchois et al., 2005; Sun et al., 2004).

The fisheye lens is one of the most efficient ways to establish an omnidirectional vision system. The structure of the fisheye lens is relatively dense and well-knit unlike the structure of reflector lenses which consist of two parts and are fragile. (Li et al., 2006; Ying et al., 2006). Omnidirectional vision (omni-vision) holds promise of various applications. We use a fisheye lens upwards with the view angle of 185° to build the omni-directional vision system. Although fisheye lens takes the advantage of an extremely wide angle of view, there is an inherent distortion in the fisheye image which must be rectified to recover the original image. An approach for geometric restoration of omni-vision images has to be considered since an inherent distortion exists. The mapping between image coordinates and physical space parameters of the targets can be obtained by means of the imaging principle on the fisheye lens. Firstly a method for calibrating the omni-vision system is proposed. The method relies on the utilities of a cylinder on which inner wall including several straight

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lines to calibrate the center, radius and gradient of a fisheye lens. Then we can make use of these calibration parameters for the correction of distortions. Several imaging rules are conceived for fisheye lenses. The regulations are discussed respectively and the distortion correction models are generated. An integral distortion correction approach based on these models is developed. A support vector machine (SVM) is introduced to regress the intersection points in order to get the mapping between the fisheye image coordinate and the real world coordinate. The advantage of using the SVM is that the projection model of fisheye lens which needs to be acquired from the manufacturer can be ignored.

Omni-directional vision navigation for autonomous guided vehicles (AGVs) appears definite significant since its advantage of panoramic sight with a single compact visual scene. This unique guidance technique involves target recognition, vision tracking, object positioning, path programming. An algorithm for omni-vision based global localization which utilizes two overhead features as beacon pattern is proposed. The localization of the robot can be achieved by geometric computation on real-time processing. Dynamic localization employs a beacon tracker to follow the landmarks in real time during the arbitrary movement of the vehicle. The coordinate transformation is devised for path programming based on time sequence images analysis. The beacon recognition and tracking are a key procedure for an omni-vision guided mobile unit. The conventional image processing such as shape decomposition, description, matching and other usually employed technique are not directly applicable in omni-vision. Vision tracking based on various advanced algorithms has been developed. Particle filter-based methods provide a promising approach to vision-based navigation as it is computationally efficient, and it can be used to combine information from various sensors and sensor features. A beacon tracking-based method for robot localization has already been investigated at the Tianjin University of Technology, China. The method utilizes the color histogram, provided by a standard color camera system, in finding the spatial location of a robot with highest probability (Musso & Oudjane, 2000; Menegatti et al., 2006).

Particle filter (PF) has been shown to be successful for several nonlinear estimation problems. A beacon tracker based on Particle Filter which offers a probabilistic framework for dynamic state estimation in visual tracking has been developed. We independently use two Particle Filters to track double landmarks but a composite algorithm on multiple objects tracking conducts for vehicle localization. To deal with the mass operations of vision tracking, a processor with the ability of effective computation and low energy cost is required. The Digital Signal Processor fits our demands, which is well known for powerful operation capability and parallel operation of instruction (Qi et al., 2005). It has been widely used in complicated algorithm calculation such as video/imaging processing, audio signal analysis and intelligent control. However, there are few cases that DSP is applied in image tracking as the central process unit. In our AGV platform, DSP has been implemented as a compatible on-board imaging tracker to execute the Particle Filter algorithm. An integrated autonomous vehicle navigator based on the configuration with Digital Signal Processor (DSP) and Filed-programmable Gate Array (FPGA) has been implemented. The tracking and localization functions have been demonstrated on experimental platform.

2. Calibration for fisheye lens camera

According to the fisheye imaging characteristics (Wang, 2006), the rectification of the fisheye image consists of two main phases. First the center of fisheye lens need to be calibrated.

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Second, establish the mapping between the physical space coordinate and fisheye images coordinate.

The approach for geometric restoration of omni-vision images has been considered in some papers since the fisheye lens was used (Cao et al., 2007). Some parameters are primarily important in the geometric restoration, such as the center and focal length of the fisheye lens. The calibration by using distortion models has been discussed in recent papers (Wang et al., 2006; Li et al., 2006; Brauer-Burchardt. & Voss., 2001). The calibration parameters can be retrieved by the method of least square and mathematic models. The previous approach utilizes grids, which are drawn on a plan surface. The grids will distort after grabbed by the fisheye lens camera (Hartley & Kang, 2007). Here, another method for calibrating the center of omni-vision images is proposed.

If a straight line in physical space is parallel to the optical axis direction of the fisheye lens, the line will not distort in the fisheye image. Therefore, a cylinder model is proposed in this article. To construct the cylinder model, straight lines are drawn on the inner side of the cylinder, whose axis is parallel to the optical axis of the fisheye camera. Then enclose the camera lens with this cylinder. The image captured with fisheye camera using cylinder model is shown in Fig. 1. The intersection of all the lines is the fisheye lens center.

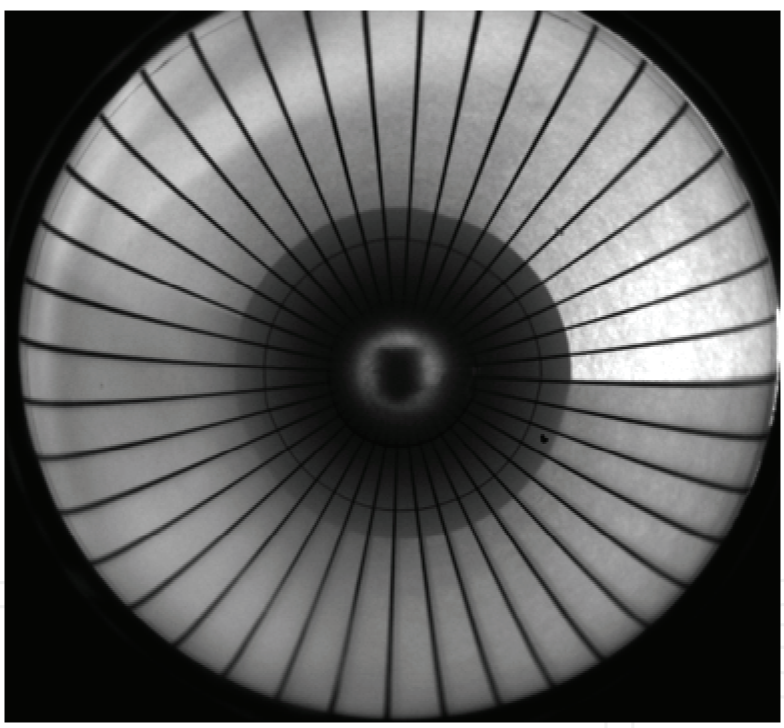

Fig. 1. Radial straight lines in fisheye lens image under cylinder model

To get the conversion relationship between the physical space coordinate and fisheye images coordinate, the following method is utilized. The lower vertex of the vertical strip which lies in the middle of the image is on the center of the fisheye optical projection that is the origin of the fisheye coordinate system as shown in Fig. 2. The horizontal strips have the same intervals and the intersection points of the vertical and horizontal strips have the equal radial distance between them in physical space. As a result of fisheye distortion, the distance between two consecutive intersection points are not equal in the image. But the corresponding coordinates of intersection points in the fisheye image is achieved.

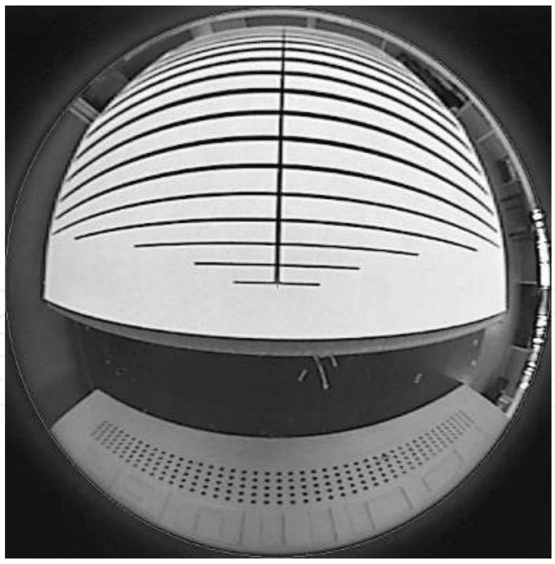

Fig. 2. Calibration for omnidirectional vision system

Then we use a support vector machine (SVM) to regress the intersection points in order to get the mapping between the fisheye image coordinate and the undistorted image coordinate. The advantage of using the SVM is that the projection model of fisheye lens which needs to be acquired from the manufacturer can be ignored.

3. Rectification for fisheye lens distortion

3.1 Fisheye Lens Rectification principle

The imaging principle of fisheye lens is different from that of a conventional camera. The inherent distortion of the fisheye lens is induced when a 2π steradian hemisphere is projected onto a plane circle. Lens distortion can be expressed as (Wang et al., 2006):

$$\begin{cases} u_d = u + \delta_u(u,v) \\ v_d = v + \delta_v(u,v) \end{cases} \tag{1}$$

Where u and v refer to the unobservable distortion-free image coordinates; u_d and v_d are the corresponding image with distortion; $\delta_u(u,v)$ and $\delta_v(u,v)$ are distortion in u and v direction.

Fisheye lens distortion can be classified into three types: radial distortion, decentering distortion and thin prism distortion. The first just arise the radial deviation. The other two produce not only the radial deviation but decentering deviation.

Generally, radial distortion is considered to be predominant, which is mainly caused by the nonlinear change in radial curvature. As a pixel of the image move along projection, the further it gets from the center of the lens, the larger the deformation is.

Owing to the different structure of lens, there are two types of deformation; one is that the proportion becomes greater while the range between the points and the center of radial distortion becomes bigger. The other is contrary. The mathematical model is as follow (Wang et al., 2006):

$$\begin{cases} \delta_{ur}(u,v) = u\left(k_1 r^2 + k_2 r^4 + k_3 r^6 + \cdots\right) \\ \delta_{vr}(u,v) = v\left(k_1 r^2 + k_2 r^4 + k_3 r^6 + \cdots\right) \end{cases} \tag{2}$$

Where k_1, k_2, k_3 are radial distortion coefficients; r is the distance from point (u, v) to the center of radial distortion.

The first term is predominant, and the second and third terms are usually negligible, so the radial distortion formula can usually be reduced as (Wang et al., 2006):

$$\begin{cases} \delta_{ur}(u,v) = k_1 u r^2 \\ \delta_{vr}(u,v) = k_1 v r^2 \end{cases} \tag{3}$$

Here, we just consider radial distortion, others are neglected. Let (u,v) be the measurable coordinates of the distorted image points, (x,y) be the coordinates of the undistorted image points, and the function f be the conversion relationship, which can be expressed as:

$$\begin{cases} x = f(u,v) \\ y = f(u,v) \end{cases} \tag{4}$$

Thus, the relationship between the fisheye image coordinate and physical world image coordinate is obtained.

3.2 Fisheye lens image rectification algorithm

In the conventional method, the approach to get parameters of distortion is complicated and the calculation is too intensive. Support Vector Machines (SVM) is statistical machine learning methods which perform well at density estimation, regression and classification (Zhang et al., 2005). It suits for small size example set. It finds a global minimum of the actual risk upper bound using structural risk minimization and avoids complex calculation in high dimension space by kernel function. SVM map the input data into a high-dimensional feature space and finds an optimal separating hyper plane to maximize the margin between two classes in this high-dimensional space. Maximizing the margin is a quadratic programming problem and can be solved by using some optimization algorithms (Wang et al., 2005). The goal of SVM is to produce model predicts the relationship between data in the testing set.

To reduce the computation complexity, we employ SVM to train a mapping from fisheye image coordinate to the undistorted image coordinate. SVM trains an optimal mapping between input date and output data, based on which the fisheye lens image can be accurately corrected.

In order to rectify fisheye image we have to get radial distortion on all of distorted image points. Based on the conversion model and the great ability of regression of SVM, we select a larger number of distorted image points (u,v) and input them to SVM. SVM can calculate the radial distortion distance and regress (u,v) to (x,y) (the undistorted image point); so that the mapping between the distortional images point and the undistorted image point can be obtained. The whole process of fisheye image restoration is shown in Fig. 3.

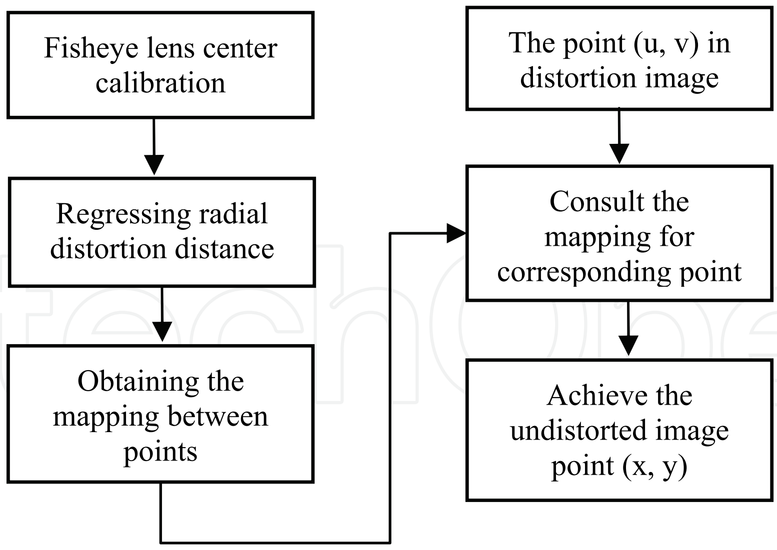

Fig. 3. Flow chart of fisheye image restoration algorithm

A number of experiments for fisheye lens image rectification have been implemented. By comparison, the results verify the feasibility and validity of the algorithm. The results are shown in Fig. 4.

Fig. 4. A fisheye image (above) and the corrected result of a fisheye image (below)

4. Omni-vision tracking and localization based on particle filter

4.1 Beacon recognition

Selecting landmark is vital to the mobile robot localization and the navigation. However, the natural sign is usually not stable and subject to many external influences, we intend to use indoor sign as the landmark. According to the localization algorithm, at least two color landmarks are requested which are projected on the edge of the AGV moving area. We can easily change the size, color and the position of the landmarks. The height of two landmarks and the distance between them are measured as the known parameters. At the beginning of tracking, the tracker has to determine the landmark at first. In our experiment, we use Hough algorithm to recognize the landmark at the first frame as the prior probability value. The Hough transform has been widely used to detect patterns, especially those well parameterized patterns such as lines, circles, and ellipses (Guo et al., 2006). Here we utilize DSP processor which has high speed than PC to perform the Circular Hough Transform. The pattern recognition by using CHT (Circular Hough Transform) is shown in Fig. 5.

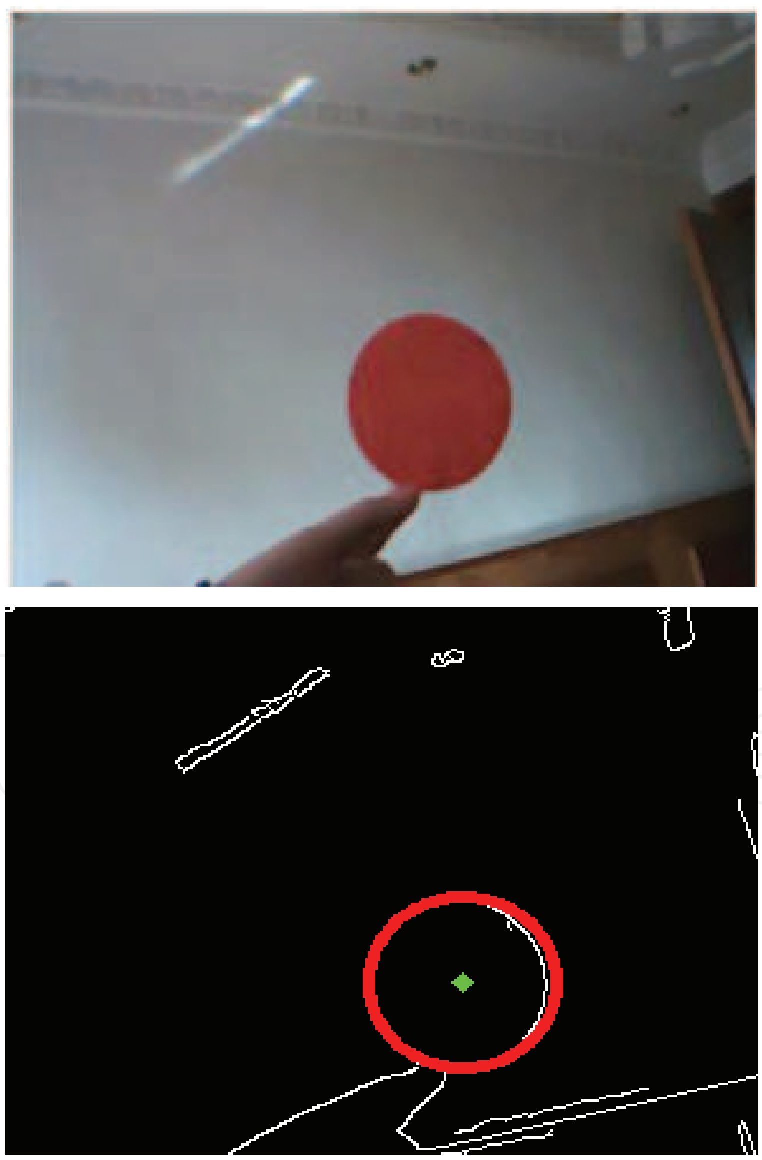

Fig. 5. A circle object (above) and the result of Circular Hough Transform (below)

4.2 Tracking based on particle filter

After obtain the initialization value, the two particle filters will track the landmark continuously. Particle filtering is a Monte Carlo sampling approach to Bayesian filtering. The main idea of the particle filter is that the posterior density is approximated by a set of discrete samples with associated weights. These discrete samples are called particles which describe possible instantiations of the state of the system. As a consequence, the distribution over the location of the tracking object is represented by the multiple discrete particles (Cho et al., 2006).

In the Bayes filtering, the posterior distribution is iteratively updated over the current state X_t, given all observations $Z_t = \{Z_1, ..., Z_t\}$ up to time t, as follows:

$$p(X_t \mid Z_t) = p(Z_t \mid X_t) \cdot \int_{x_{t-1}} p(X_t \mid X_{1:t-1}) \cdot p(X_{t-1} \mid Z_{t-1}) dx_{t-1} \tag{5}$$

Where $p(Z_t \mid X_t)$ expresses the observation model which specifies the likelihood of an object being in a specific state and $p(X_t \mid X_{t-1})$ is the transition model which specifies how objects move between frames. In a particle filter, prior distribution $p(X_{t-1} \mid Z_{t-1})$ is approximated recursively as a set of N-weighted samples, which is the weight of a particle. Based on the Monte Carlo approximation of the integral, we can get:

$$p(X_t \mid Z_t) \approx kp(Z_t \mid X_t) \sum_{i=1}^{N} w_{t-1}^{(i)} p(X_t \mid X_{t-1}^{(i)}) \tag{6}$$

The principal steps in the particle filter algorithm include:

STEP 1 Initialization

Generate particle set from the initial distribution $p(X_0)$ to obtain $\{X_0^{(i)}, w_0^{(i)}\}_{i=1}^{N}$, and set $k = 1$.

STEP 2 Propagation

For $i = 1, ..., N$, Sample $X_k^{(i)}$ according to the transition model $p(X_k^{(i)} \mid X_{k-1}^{(i)})$.

STEP 3 Weighting

Evaluate the importance likelihood

$$w_k^{(i)} = \frac{w_k^{(i)}}{\sum_{j=1}^{N} w_k^{(j)}} \qquad i = 1, ..., N \tag{7}$$

STEP 4 Normalize the weights

$$w_k^{(i)} = p(Z_k \mid X_k^{(i)}) \qquad i = 1, ..., N \tag{8}$$

Output a set of particles $\{X_k^{(i)}, w_k^{(i)}\}_{i=1}^{N}$ that can be used to approximate the posterior distribution as

$$p(X_k \mid Z_k) = \sum_{i=1}^{N} w_k^{(i)} \delta(X_k - X_k^{(i)}) \tag{9}$$

Where $\delta(g)$ is the Dirac delta function.

STEP 5 Resample particles $X_k^{(i)}$ with probability $w_t^{(i)}$ to obtain N independent and identically distributed random particles $X_k^{(j)}$ approximately distributed according to $p(X_k \mid Z_k)$.

STEP 6 Set $k = k + 1$, and return to STEP 2.

4.3 Omni-vision based AGV localization

In this section, we will discuss how to localize the AGV utilizing the space and image information of landmarks. As it is shown in Fig. 6, two color beacons which are fixed on the edge of the AGV moving area as landmarks facilitate navigation. The AGV can localize itself employing the fisheye lens camera on top of it.

The height of two landmarks and the distance between them are measured as the known parameters. When the AGV is being navigated two landmarks are tracked by two particle filters to get the landmarks positions in the image.

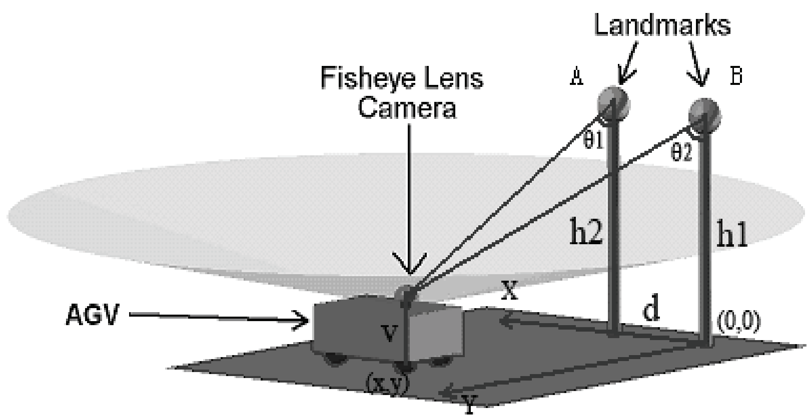

Fig. 6. Physical space coordinates system for landmarks localization

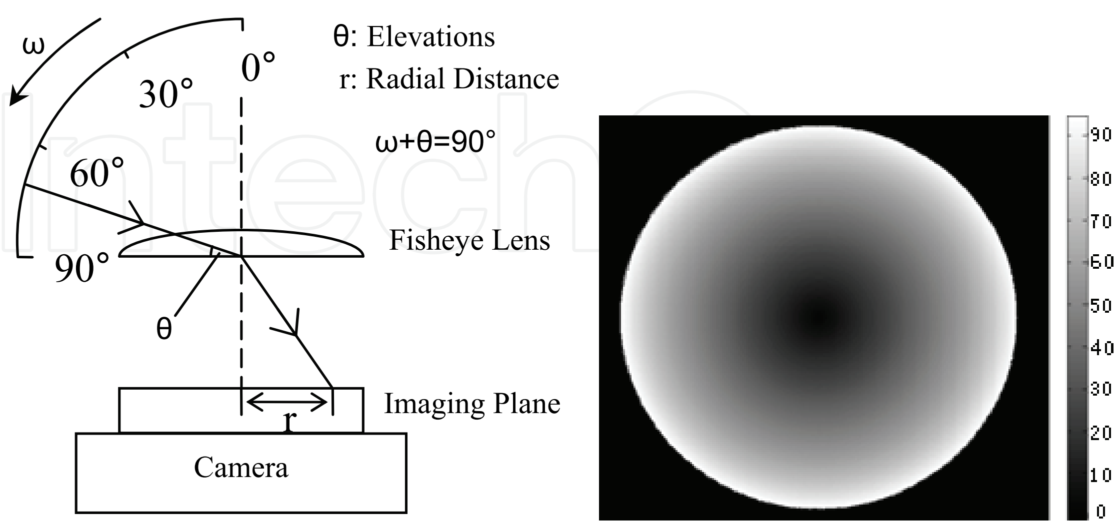

Fig. 7. Left figure shows that the relationship between incident angles and radial distances of fisheye lens. Right figure illustrates the values of corresponding incident angles with different grey levels in the whole area of fisheye sphere image

According to the Equal Distance Projection Regulation, the angle of view ω corresponds with the radial distance r between projection point and projection center. As shown in Fig. 7, the mapping between ω and r can be established. Based on this mapping, the image coordinate and space angle of the landmark are connected.
Utilizing the depressions obtained from images and demarcated parameters of landmarks, the physical space position of the AGV is confirmed. We tag the landmarks as A and B. In order to set up the physical coordinate system, A is chosen as the origin. AB is set as axis X and the direction from A to B is the positive orientation of axis X. Axis Y is vertical to Axis X. According to the space geometry relations, we can get:

$$\begin{aligned} x &= \frac{[\cot\theta_1(h_1 - v)]^2 - [\cot\theta_2(h_2 - v)^2] + d^2}{2d} \\ y &= \sqrt{[\cot\theta_1(h_1 - v)^2 - x^2]} \end{aligned} \tag{10}$$

where (x, y) is the physical space coordinate of lens, “ h_1 ” and “ h_2 ” are the height of two landmarks, “ d ” is the horizontal distance between two landmarks, “ v ” is the height from ground to lens, “ θ_1 ” and “ θ_2 ” are the depression angles from landmark A and B to lens. Here, y is nonnegative. Thus the moving path of AGV should keep on one side of the landmarks, which is half of the space.

5. Navigation system

5.1 Algorithm architecture of navigator

A dynamic omni-vision navigation technique for mobile robots is being developed. Navigation functions involve positional estimation and surrounding perception. Landmark guidance is a general method for vision navigation in structural environments. An improved beacon tracking and positioning approach based on a Particle Filter algorithm has been utilized. Some typical navigation algorithms have been already implemented such as the classic PID compensator, neural-fuzzy algorithm and so on. The multi-sensory information fusion technique has been integrated into the program. The hybrid software and hardware platform has been developed.
The algorithm architecture of the on-board navigator, as shown in Fig. 8, consists of the following phases: image collection, image pre-processing, landmark recognition, beacon tracking, vehicle localization and path guidance. The image distortion correction and recovery for omni-vision is a critical module in the procedures, which provides coordinate mapping for position and orientation.

5.2 Hardware configuration of navigator

The design of the navigator for mobile robots depends on considering the integration of the algorithm and hardware. Real-time performance is directly influenced by the results of localization and navigation. Most image processing platforms use a PC and x86 CPUs. This presents some limitations for an on-board navigator for vehicles because of redundancy resources, energy consuming and room utility.
This article presents a compatible embedded real-time image processor for AGVs by utilizing a Digital Signal Processor (DSP) and Field-Programmable Gate Array (FPGA) for the image processing component. The hardware configuration of the navigator is shown in Fig. 9.

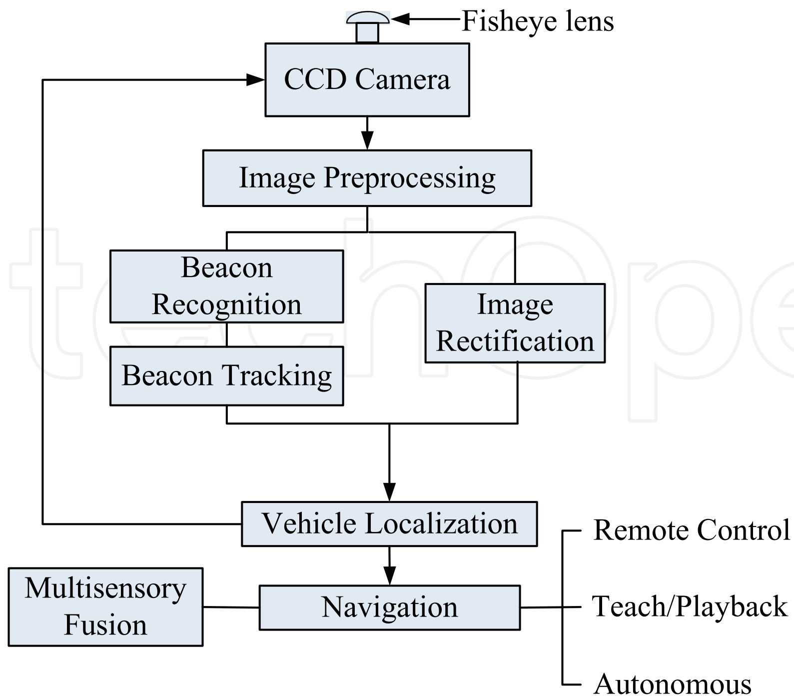

Fig. 8. The algorithm architecture of the navigator

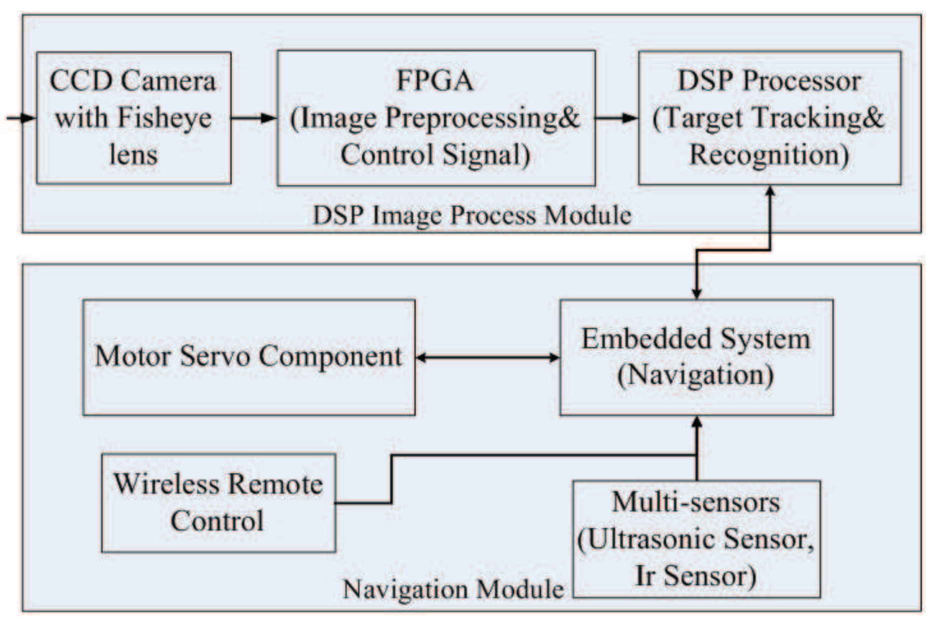

Fig. 9. Hardware configuration of the unique navigator

The DSP facilitates Enhanced DMA (EDMA) to transfer data between the DSP and external Navigation Module efficiently. Pipeline and code optimization are also required to move to sharply increase the speed. An efficient FPGA preprocessing uses binarized images with a given threshold before starting processing and also provides some necessary trigger signal functions. With this coprocessor, it is possible to accelerate all navigator processes. The DSP and FPGA can cooperate with each other to solve the real-time performance problems; the flexible frame is reasonable and practical.

The navigation module consists of an embedded platform, multi-sensors and an internet port. The embedded system is employed for a navigation platform, which consists of the following functions: vehicle localization, line following path error correction, obstacle avoidance through multi-sensory capability. There are three operation modes: remote control, Teach/Playback and autonomous. The internet port provides the wireless communication and human-computer interaction. The motor servo system is utilized for motion control. With the prototype we have obtained some satisfying experimental results.

6. Experimental result

The final system has been implemented by utilizing a real omni-directional vision AGV in an indoor environment which has been verified in terms of both the practicability and the feasibility of the design. The prototype experimental platform is shown in Fig. 10.

Fig. 10. Experimental autonomous guided vehicle platform

We perform the experiments twice to show the result. Two beacons with different colors are placed on the roof as landmarks. A color histogram was uses as the feature vector in particle filters. The experimental area we choose is about 30 square meters. The height of Landmarks A and B are 2.43m and 2.46m, respectively. The distance between them is 1.67m. The height of lens is 0.88m. At the initialization, the original positions of landmarks in the image are set for the tracker. The AGV guided by double color landmarks shown in Fig. 11. Driving path and orientation shown in Fig. 12. We can see the localization results are dispersed on the both sides of the moving path. The Fig. 12 demonstrates the results of AGV orientation corresponding to the positions in left figures from each localization cycle. The totally 16 fisheye images that were picked up are shown in Fig. 13 and Fig. 14. The numerical localization results are listed in the Table 1 and Table 2.

Fig. 11. Localization of the experimental AGV platform

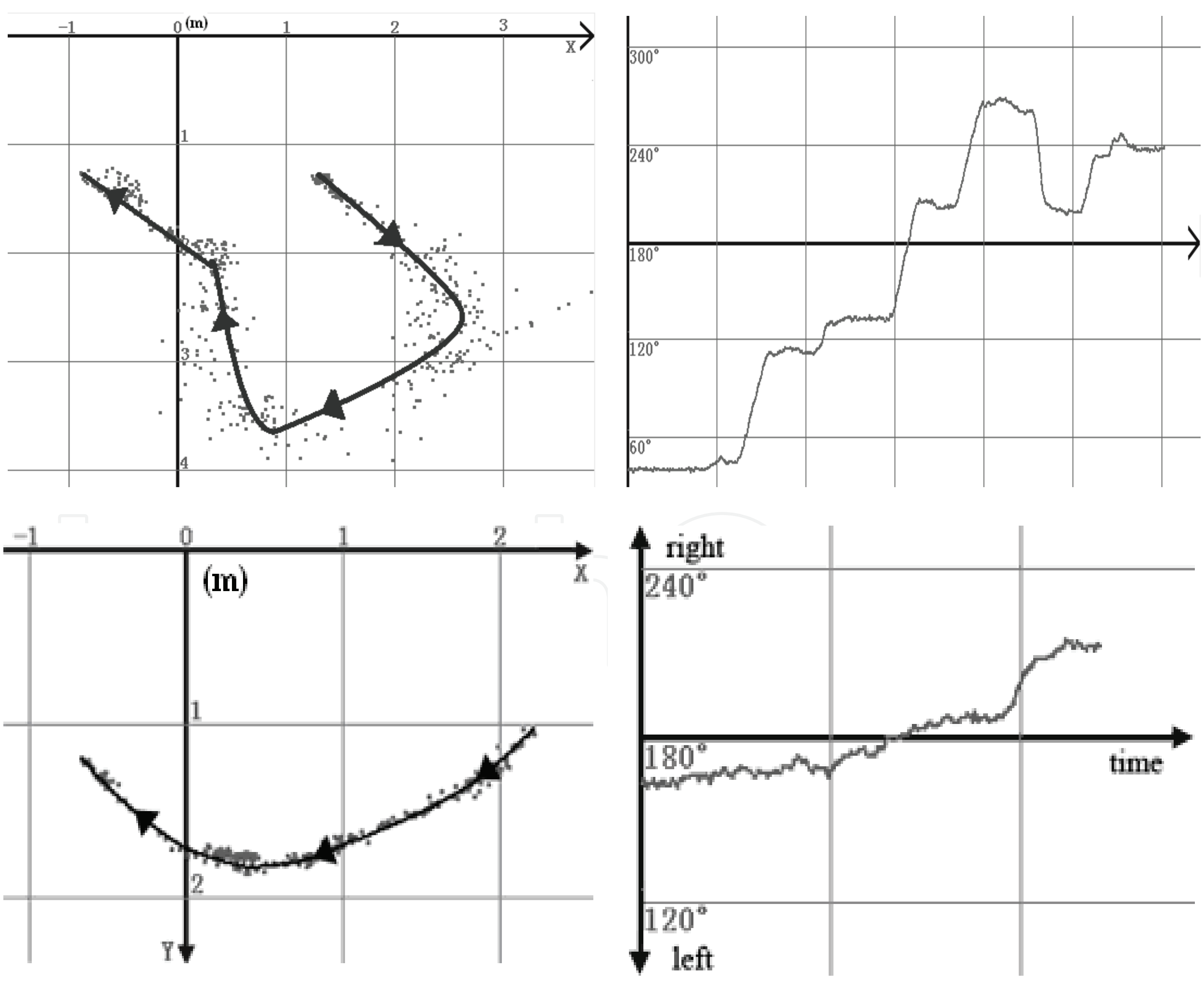

Fig. 12. Localization and orientation of autonomous vehicle in experiment 1 (above) and 2 (below) (the units are meter and degree (angle))

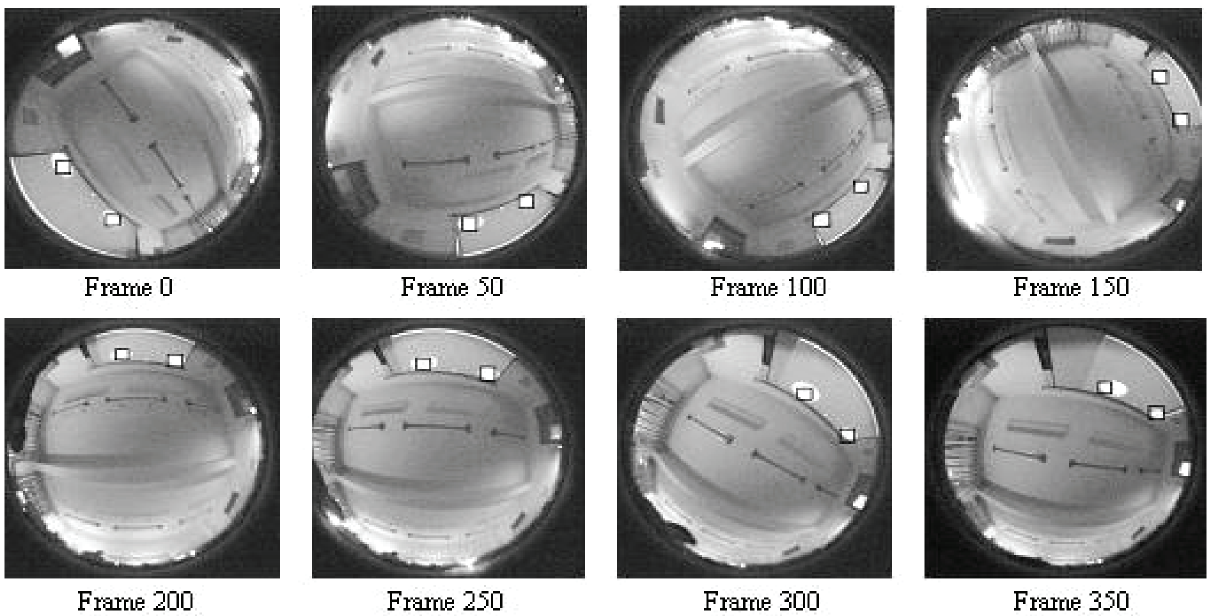

Fig. 13. Results of dynamic beacon tracking based on particle filters in experiment 1

(x, y, ф)	1	2	3	4
Actual Coordinates	(1.31, 1.35, 45°)	(2.00, 1.88, 68°)	(2.46, 2.67, 74°)	(2.34, 2.93, 144°)
Localization Coordinates	(1.47, 1.33, 43°)	(2.32, 1.93, 66°)	(2.33, 2.69, 79°)	(2.38, 2.96, 148°)
(x, y, ф)	5	6	7	8
Actual Coordinates	(1.35, 3.45, 162°)	(0.66, 3.00, 271°)	(0.00,1.94, 135°)	(-0.92, 1.33, 137°)
Localization Coordinates	(1.38, 3.47, 160°)	(0.68, 3.06, 276°)	(-0.18, 2.00, 132°)	(-0.88, 1.29, 135°)

Table 1. Localization results of experiment 1(units are meter and degree (angle))

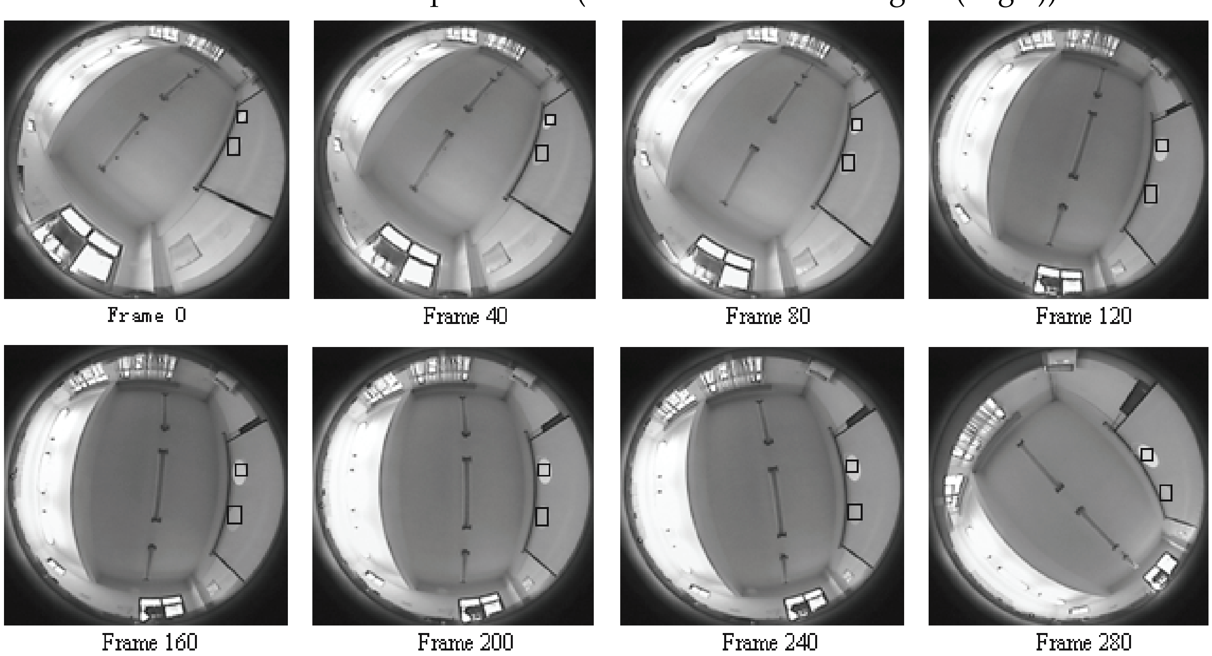

Fig. 14. Results of dynamic beacon tracking based on particle filters in experiment 2

(x, y, ф)	1	2	3	4
Actual Coordinates	(2.12, 1.06, 166°)	(2.05, 1.21,168°)	(1.53, 1.58,173°)	(1.07, 1.75, 176°)
Localization Coordinates	(2.23, 1.07, 165°)	(2.00, 1.18, 168°)	(1.55, 1.52,171°)	(1.00, 1.78 178°)
(x, y, ф)	5	6	7	8
Actual Coordinates	(0.52,1.93,179°)	(0.06,1.73,188°)	(-0.32,0.51,211°)	(-0.78,1.22,218°)
Localization Coordinates	(0.50,1.90,180°)	(0.00,1.70,191°)	(-0.35,0.50,210°)	(-0.75,1.20,220°)

Table 2. Localization results of experiment 2(units are meter and degree (angle))

7. Conclusion

We establish omni-directional vision system with fisheye lens and solve the problem of fisheye image distortion. A method for calibrating the omni-vision system is proposed to generate the center of a fisheye lens image. A novel fisheye image rectification algorithm based on SVM, which is different from the conventional method is introduced. Beacon recognition and tracking are key procedures for an omni-vision guided mobile unit. A Particle Filter (PF) has been shown to be successful for several nonlinear estimation problems. A beacon tracker based on a Particle Filter which offers a probabilistic framework for dynamic state estimation in visual tracking has been developed. Dynamic localization employs a beacon tracker to follow landmarks in real time during the arbitrary movement of the vehicle. The coordinate transformation is devised for path programming based on time sequence images analysis. Conventional image processing such as shape decomposition, description, matching, and other usually employed techniques are not directly applicable in omni-vision. We have implemented the tracking and localization system and demonstrated the relevance of the algorithm. The significance of the proposed research is the evaluation of a new calibration method, global navigation device and a dynamic omni-directional vision navigation control module using a beacon tracker which is based on a particle filter through a probabilistic algorithm on statistical robotics. An on-board omni-vision navigator based on a compatible DSP configuration is powerful for autonomous vehicle guidance applications.

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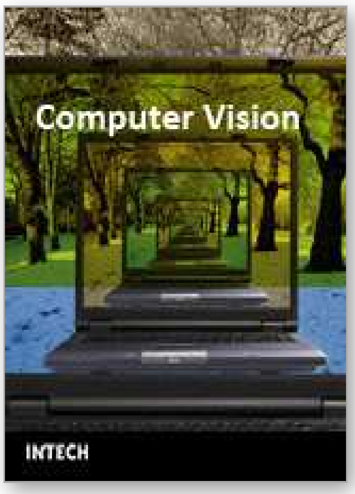

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This book presents research trends on computer vision, especially on application of robotics, and on advanced approachs for computer vision (such as omnidirectional vision). Among them, research on RFID technology integrating stereo vision to localize an indoor mobile robot is included in this book. Besides, this book includes many research on omnidirectional vision, and the combination of omnidirectional vision with robotics. This book features representative work on the computer vision, and it puts more focus on robotics vision and omnidirectioal vision. The intended audience is anyone who wishes to become familiar with the latest research work on computer vision, especially its applications on robots. The contents of this book allow the reader to know more technical aspects and applications of computer vision. Researchers and instructors will benefit from this book.

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