2009 Fifth International Conference on Natural Computation

Beacon Tracking with an Embedded Omni-vision System

Huazhu Fu
School of Mechanical Engineering
Tianjin University of Technology
Tianjin 300384, P.R. China
fuhuazhu@163.com

Zuoliang Cao
School of Mechanical Engineering
Tianjin University of Technology
Tianjin 300384, P.R. China
zlcao@126.com

Juha Röning
Electrical and Information Engineering
University of Oulu
FIN-90014, Finland
juha.roning@ee.oulu.fi

***Abstract*—This paper presents an embedded omni-vision navigation system which involves beacon tracking and vehicle localization. A new tracking algorithm, the Feature Matching Embedded Particle Filter, is proposed. A global localization method for omni-vision based on coordinate transformation is also proposed. The Digital Signal Processor (DSP) provides a hardware platform for an on-board tracker. Our dynamic navigator employs the DSP tracker to follow landmarks in real time during the arbitrary movement of the vehicle and computes its position for localization based on time sequence images analysis. Experimental results demonstrated that the navigation system can efficiently offer the vehicle guidance.**

***Keywords*-omni-vision; multi-object tracking; embedded; Particle Filter;**

I. Introduction

Omni-directional vision has been used for Autonomous Guided Vehicles (AGV) navigation thanks to its advantage of acquiring a hemispherical view with one look. It is easier for a fisheye lens to find and track features since they stay longer in its 180o field of view of the environment. Extremely wide angle optical image equipment called fisheye lens is one of the most efficient ways to establish omni-directional vision system [1], [2], [3].

The efficient tracking with fisheye lens for AGV in complex environments is a challenging task for the vision community. Particle Filter, which is based on the theory of Bayesian correlation, provides a promising approach to vision based navigation, as it is computationally efficient and can be used to combine (or fuse) information from various sensors [4], [5]. In this paper, we improved Particle Filter to a new algorithm, the Feature Matching Embedded Particle Filter (FMEPF), to integrate advantages of particle filter and feature matching.

In order to track a moving object in real-time without delay or loss of the image data, a processor with the ability of effective computation and low energy cost is required. The Digital Signal Processor (DSP) fits our demands, since it is well known for powerful operation capability and parallel operation of instructions. It has been widely used in complicated algorithm calculation such as video/imaging processing, audio signal analysis and intelligent control. In our AGV platform, we transplanted the tracking algorithm into DSP Processor, as a compatible on-board multi-object tracker for AGV navigation.

II. The Feature Matching Embedded Particle Filter

To localize the AGV with landmarks, vision tracking is firstly used to obtain the image coordinates of the landmark in movement. In this paper, we propose a new tracking algorithm, the Feature Matching Embedded Particle Filter (FMEPF), to combine Particle Filter and feature matching for object tracking, integrating advantages of the two methods.

Particle Filter is a Monte Carlo sampling approach to Bayesian filtering, where the probability density is represented by a set of weighted samples (called particles). These samples 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 [4].

In the Bayes filtering, the posterior distribution is iteratively updated over the current state X_k, given all observations $Z_k = \{Z_1, \ldots, Z_k\}$ up to time k, as follows:

$$p(x_k|z_{1:k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|z_{1:k-1})dx_{k-1} \quad (1)$$

$$p(x_k|z_{1:k}) = \frac{p(z_k|x_k)p(x_k|z_{1:k-1})}{p(z_k|z_{1:k-1})} \quad (2)$$

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

$$p(X_k|Z_k) \approx kp(Z_k|X_k)\sum_{i=1}^{N} w_{k-1}^{(i)} p(X_k|X_{k-1}^{(i)}) \quad (3)$$

In experiments, if a target moves with speed or haste, the Particle Filter tracking window might drift. Otherwise the precision and stability is related with the particle number,

978-0-7695-3736-8/09 $25.00 © 2009 IEEE
DOI 10.1109/ICNC.2009.296

the large number would bring massive calculation and reduce efficiency. So we improved Particle Filter as FMEPF algorithm, the Particle Filter is only used as the probabilistic framework to track a region of interested (ROI), and then the feature matching is applied in this ROI. The size of the ROI could be set based on the velocity of the target.Finally the location of the tracking object is represented by the result of matching.

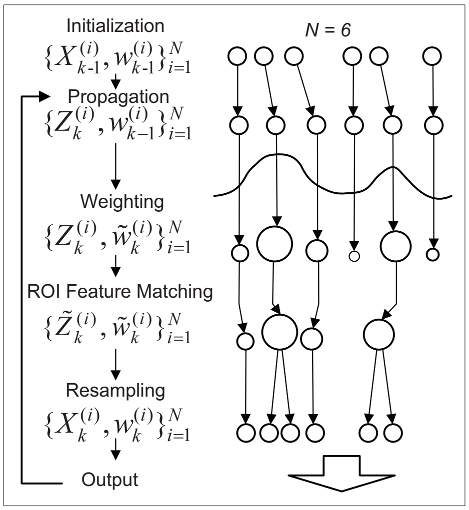

Figure 1. The Flowchart on targets tracking using FMEPF

The general operation of the multi-object tracker based on FMEPF is illustrated in Figure 1.

STEP 1 Initialization

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

STEP 2 Propagation

For $i = 1, \ldots, N.$, Sample $Z_k^{(i)}$ according to the transition model $p(Z_k^{(i)}|X_{0:k-1}^{(i)})$.

STEP 3 Weighting

Calculate the importance weight likelihood:

$$\tilde{w}_k^{(i)} = w_{k-1}^{(i)} p(Z_k|X_k^{(i)}) \qquad i = 1, \ldots, N. \tag{4}$$

Normalize the weights:

$$w_k^{(i)} = \frac{\tilde{w}_k^{(i)}}{\sum\limits_{j=1}^{N} \tilde{w}_k^{(j)}} \qquad i = 1, \ldots, N. \tag{5}$$

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

$$p(\tilde{Z}_k|Z_k) = \sum_{i=1}^{N} w_k^{(i)} \delta(X_k - X_k^{(i)}) \tag{6}$$

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

STEP 4 ROI Feature Matching

Set ROI window according $\{\tilde{Z}_k^{(i)}, w_k^{(i)}\}_{i=1}^{N}$, apply feature matching in this region and output the result as $\{X_k^{(i)}, w_k^{(i)}\}_{i=1}^{N}$ the target distribution.

STEP 5 Resampling

Resample the new 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 $p(X_k|Z_k)$.

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

III. Localization for Vehicle with Fisheye lens

Double landmarks are fixed on the edge of the AGV moving area. The height of two landmarks and the distance between them are measured as the known parameters. The landmark's coordinates in the fisheye image system are the only information that the guidance can get from the environment. When the AGV is being navigated, the fisheye lens is plumbed and placed on the top of the AGV and two landmarks are tracked by a multi-object tracker to get the landmarks positions in the image.

According to the Equidistance Projection Theorem [6], the angle of view w corresponds with the radial distance r between projection point and projection center. As shown in Figure 2, the mapping between w and r can be established. Based on this mapping, the image coordinate and space angle of the landmark are connected.

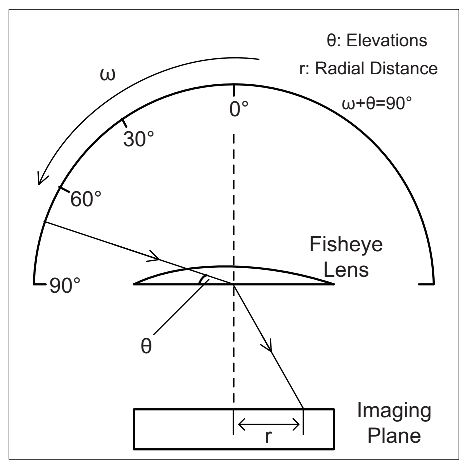

Figure 2. The Equidistance Projection Model

As Figure 3 shows, we can calculate the physical space coordinates of the Vehicle (X_0, Y_0) as:

$$\begin{cases} X_0 = -\frac{(h_1-v)(X_1''-X_0'')\cos\theta}{r_1\tan(\theta_1)} + \frac{(h_1-v)(Y_1''-Y_0'')\sin\theta}{r_1\tan(\theta_1)} + X_1 \\ Y_0 = -\frac{(h_1-v)(X_1''-X_0'')\sin\theta}{r_1\tan(\theta_1)} - \frac{(h_1-v)(Y_1''-Y_0'')\cos\theta}{r_1\tan(\theta_1)} + Y_1 \end{cases} \tag{7}$$

where the (X_i'', Y_i'') is landmark coordinates in the fisheye image, the (X_0'', Y_0'') is the center of fisheye lens, the

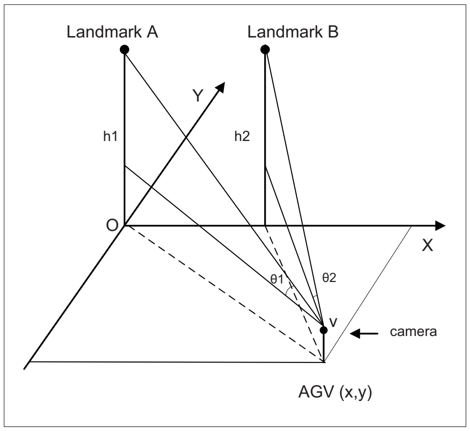

Figure 3. The space structure for landmarks localization

(X_0, Y_0) is the AGV physical space coordinates. h_1 is the height of landmark A, v is the height from ground to lens, (X_1'', Y_1'') and (X_2'', Y_2'') are the image coordinates of two landmarks. The θ which is the horizontal direction of AGV in space coordinate system could be obtained from the fisheye image coordinate system as shown in Figure 4:

$$\theta = \begin{cases} -\arctan\left(\dfrac{Y_1'' - Y_2''}{X_1'' - X_2''}\right) & X_1'' < X_2'' \\ \pi - \arctan\left(\dfrac{Y_1'' - Y_2''}{X_1'' - X_2''}\right) & X_1'' > X_2'' \; and \; Y_1'' \geq Y_2'' \\ -\arctan\left(\dfrac{Y_1'' - Y_2''}{X_1'' - X_2''}\right) - \pi & X_1'' > X_2'' \; and \; Y_1'' \leq Y_2'' \\ \pi/2 & X_1'' = X_2'' \; and \; Y_1'' > Y_2'' \\ -\pi/2 & X_1'' = X_2'' \; and \; Y_1'' < Y_2'' \end{cases} \tag{8}$$

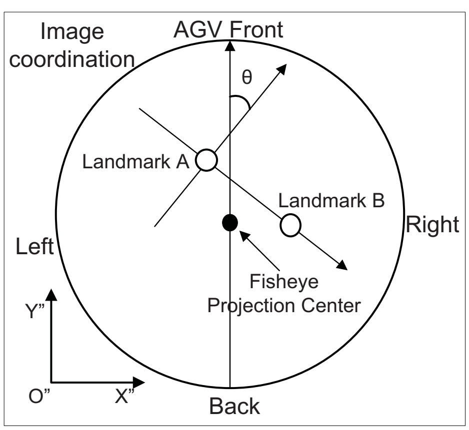

Figure 4. The coordinates system of the fisheye image.

IV. Hardware configuration on DSP tracker

For localization, we often need more than two landmarks to track and the computation of multi-object tracking is difficult to satisfy with the common CPU based on x86 structure. On the other hand, the navigator is used for a mobile robot which require small volume and low power dissipation. Therefore, we present a compatible embedded real-time image-processing platform for the navigation system by utilizing Digital Signal Processor (DSP). We choose the TMS320C6437 DSP of Texas Instruments, which is the one of the TMS320C64x+ DSPs series. The DM6437 device is a third-generation high performance fixed-point DSP, which is good at digital media applications [7]. The hardware configuration of the DM6347 circuit is shown in Figure 5:

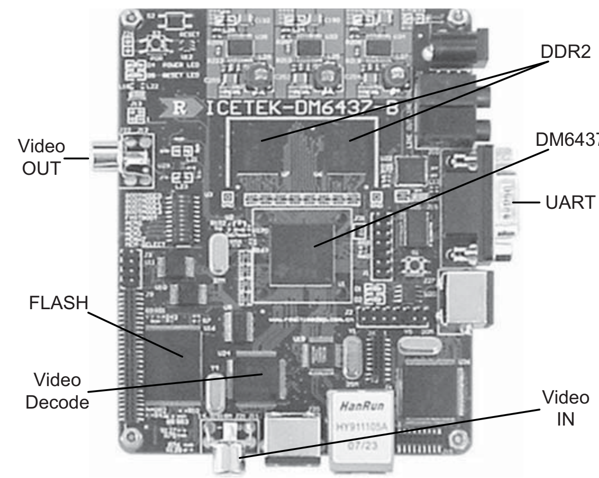

Figure 5. Hardware profile on DSP tracker

V. Experimental Results and Discussion

A. Tracking Algorithm Comparison Experiment

To illustrate the differences between the conventional particle filter and our FMEPF, we apply them to the same image sequences. The resolution of each image is 640 x 480 pixels and the tracked region is 40 x 40 pixels. We use PC for simulation test (P4 3.06GHz CPU, 512 MB memory). We apply at least 300 samples to the conventional particle filter.

As shown in Figure 6 Upper Row, the algorithm tracked target at beginning, but caused by rapid movement the tracker loses the target. Using the same observation model and dynamic model, thanks to the embedded region feature matching analysis, our tracker can maintain target tracking with fewer samples; only 100 samples needed to track target robustly. Experimental results demonstrate that our algorithm outperforms the other method, and performs well with fewer samples.

B. AGV Navigation Experiments

The navigation system has been implemented by utilizing a real omni-directional vision AGV in an indoor environ-

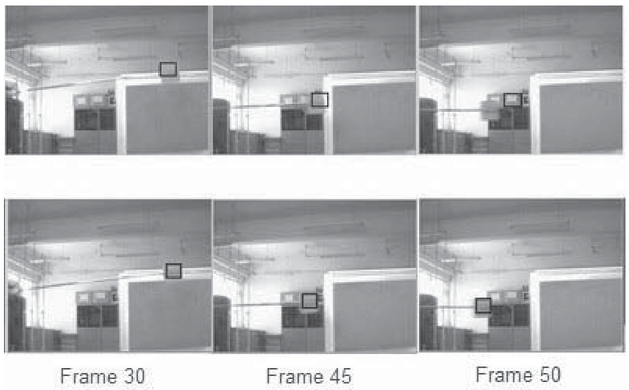

Figure 6. Comparisons between the conventional particle filter (Upper Row) and our FMEPF (Bottom Row). Tracked landmarks are marked in black squares.

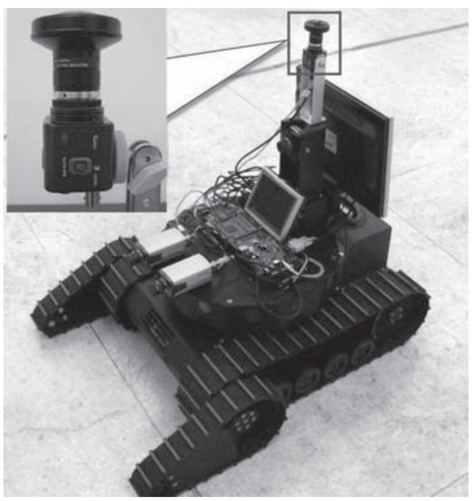

Figure 7. Experimental Autonomous Guided Vehicle with Fisheye lens.

Table I
THE LOCALIZATION RESULTS (UNIT: CM)

Sampling Point	Actual Coordinates	Localization Coordinates
Position 1	(210,-214) 14^{o}	(189,-191) 17^{o}
Position 2	(186,-160) 25^{o}	(170,-145) 23^{o}
Position 3	(159,-133) 17^{o}	(145,-125) 15^{o}
Position 4	(146,-80) 9^{o}	(130,-72) 10^{o}
Position 5	(133,-23) 6^{o}	(130,-20) 5^{o}
Position 6	(119,53) 7^{o}	(127,62) 8^{o}
Position 7	(106,105) 15^{o}	(121,122) 13^{o}
Position 8	(80,159) 11^{o}	(102,178) 14^{o}

ment. The prototype of experimental platform is shown in Figure 7.

Two beacons with different colors are hanged on the roof as landmarks. The height of Landmark A and B are 2.56m and 2.49m. The distance between them is 2.65m. The height of lens is 0.87m. The AGV moves along the path, as shown in Figure 9. We pick up 8 sampling points, shown in Figure 8. The localization results are shown in the Table I.

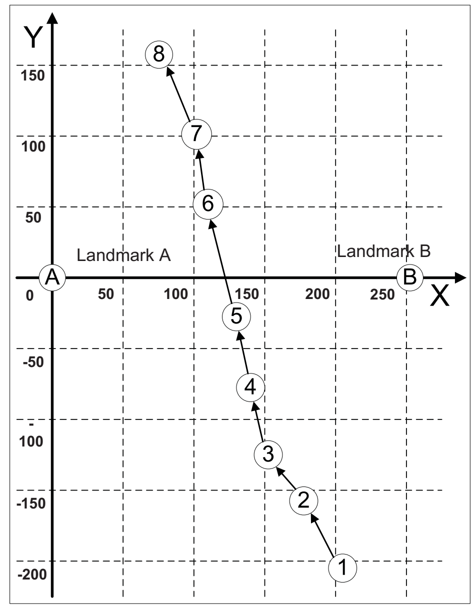

Figure 9. AGV moving Path (unit: cm) and the labels are the sampling points.

As the experiments show, the navigation system is accurate to a certain extent. The moving area has been limited by the reach of the landmarks; when the AGV is far away from a landmark, the localization would have more margin. Although fisheye lens take the advantage of an extremely wide angle of view, there is a distortion in the fisheye image, especially near the edge of the image where the distortion is more serious. When the AGV is far away from the landmark, the projection coordinates of the marks will be close the edge of the fisheye image, and several pixels tolerance caused by distortion would lead to a large mistake of localization.

To reduce this tolerance, we could set a sequence of landmarks, shown in Figure 10. As the projection point moves out of the effective coverage, the tracker recognizes the next couple of beacons in the AGV front area and refreshes the space coordinate value. This way an AGV could move longer distance and a larger area.

VI. CONCLUSION

In this paper, we built a navigation system based on omni-vision. A multi-object tracker is employed as core of guidance system. The tracker based on FMEPF algorithm could track moving multiple targets robustly and effectively, and the DSP platform has advantages of high efficiency, real time, low power consumption and small volume. We also designed an omni-vision localization method base on two landmarks, with the extremely wide angle field of view

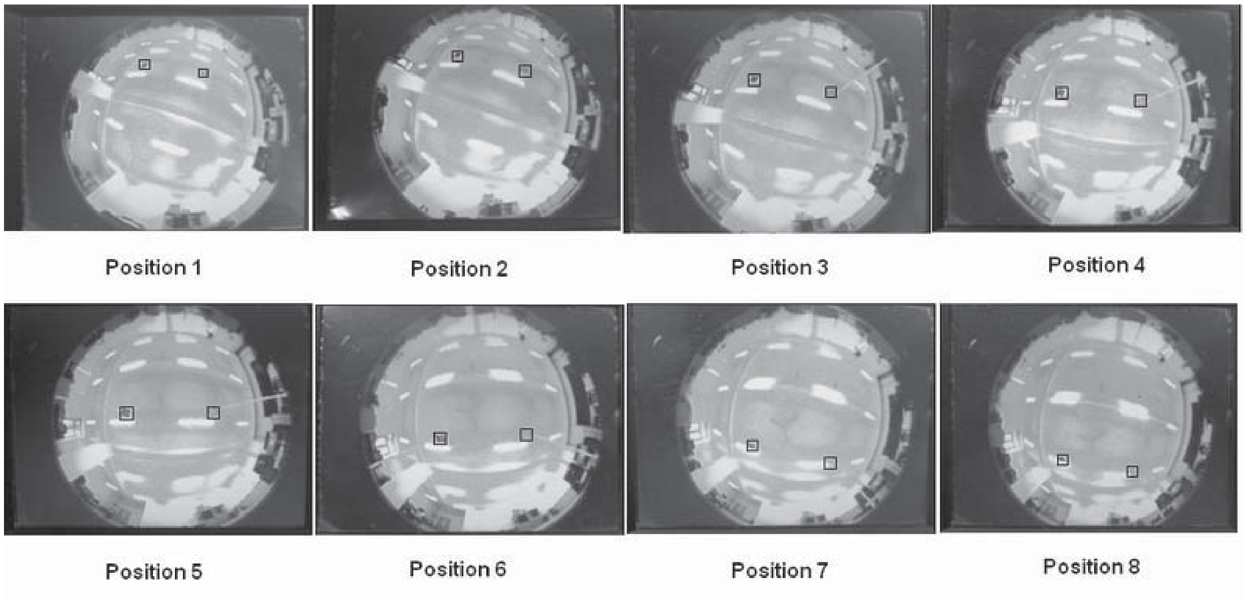

Figure 8. The Sampling Points' images of AGV navigation experiment. The images were captured from fisheye lens. In each image, the left tracking target is landmark A featured by red color, the right is landmark B featured by yellow color.

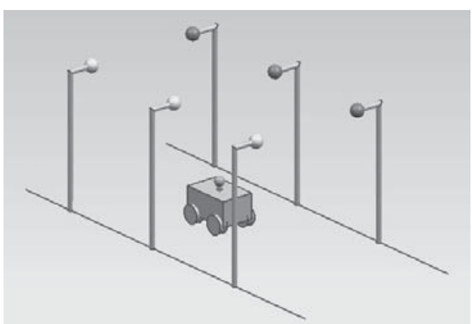

Figure 10. The Sequence Landmarks for AGV Navigation.

offered by the fisheye lens, the coordinates and orientation of the AGV could be computed. The experiment shows that the navigation system could be applied to AGV guidance, on-board mobile robot, and other related areas.

ACKNOWLEDGMENT

This paper contains the results of research of the international science and technology collaboration project of China and Finland (2006DFA12410) supported by the Ministry of Science and Technology of the People's Republic of China. Additionally, the research involves part of the "863" High-Tech Program (2007AA04Z229) supported by the Ministry of Science and Technology of the People's Republic of China.

REFERENCES

[1] Zuoliang C, Shiyu L, Roning J, "Omni-directional vision localization based on particle filter," *Image and Graphics. ICIG 2007*, pp. 478–183, 2007.

[2] O. G. Bonin-Font F, Ortiz A, "Visual navigation for mobile robots: A survey," *Journal of Intelligent and Robotic Systems*, vol. 53, no. 3, pp. 263–296, January 2008.

[3] Winters N, Gaspar J, Lacey G, Santos-Victor J, "Omni-directional vision for robot navigation," *Omnidirectional Vision. Proceedings. IEEE Workshop on*, pp. 21–28, 2000.

[4] Kotecha, J. H., Djuric, P. M., "Gaussian particle filtering," *Signal Processing, IEEE Transactions on*, vol. 51, no. 10, pp. 2592–2601.

[5] Charif, Hammadi, McKenna, Stephen, "Tracking the activity of participants in a meeting," *Machine Vision and Applications*, vol. 17, no. 2, pp. 83–93.

[6] Yongzhong Wang, *Fisheye Lens Optics*. China: China Science Press, 2006.

[7] Texas Instruments, *TMS320DM6437 Digital Media Processor*. Texas Instruments, 2008.