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Ground Texture Matching based Global Localization for Intelligent Vehicles in Urban Environment

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Abstract—**Localization is a critical problem in the research of intelligent vehicles. Traditional vision based methods suffer from reliable problems in outdoor environment, especially in complicated urban areas. This paper proposes a novel approach to localize the position of a vehicle with respect to a global map, based on the texture of the ground where the vehicle moves. Images of the ground texture are obtained from a camera viewing downward fixed on the bottom of the vehicle. Thus, the vehicle actuates like a big optical mouse. Global localization is achieved by map matching using ICP (Iterative Closest Point) algorithm. M-estimator is applied in the ICP algorithm to improve the robustness to noises. Odometry data and UKF (Unscented Kalman Filter) are utilized to address the local minimum problem in ICP and to improve the accuracy. Experimental results with both synthetic and real data prove the reliability and high accuracy of the proposed approach.**

I. Introduction

Localization, which is also known as pose estimation, is a critical problem in the research of intelligent vehicles. Lots of approaches have been proposed to solve this problem, using various types of sensors including odometry, magnetic sensors, laser radar and GPS. However, none of them could satisfy the performance and cost requirements.

Vision based system, which is light-weight, compact, relatively inexpensive and can provide abundant information, is considered as a promising approach for the research of intelligent vehicles. Although many vision based systems have been proposed over the past 20 years, localization using vision based techniques in urban environment still remains a challenge. First, the complicated illumination in outdoor environment can affect the system performance dramatically and decrease the reliability of the system, or even disable the system when the sunlight makes the camera overexposed in the morning or afternoon. Second, the roads in urban environment are complicated, for example, sharp-curve roads. Since the field of view of existing cameras is limited, the road may be lost from the field of view if the camera is mounted in the traditional looking-forward pose. The third problem is the global localization. Several vision based algorithms, such as optical flow[1] and feature based methods[2][3], have been proposed to address this problem during the past decades. The optical flow method requires extremely high computation so that it cannot satisfy the requirement by intelligent vehicles. The feature based method is usually limited in indoor application because of the difficulty in feature detection. Thus most of the successful vision based systems[4]-[6] used in outdoor application only estimate the offset of the vehicle to the desired path without giving the global location information. If an intelligent vehicle is demanded to implement complicated tasks in urban environment, its global pose must been obtained.

This paper proposed a vision based global localization method for intelligent vehicles in the urban environment aiming at addressing above problems. In order to reduce the affection of environmental condition such as light, shade and obstacles, a special camera configuration is designed. A camera viewing downward is fixed on the bottom of the vehicle and captures the image of the ground right under the vehicle. To deal with the complicated infrastructure and the global localization problem, a ground texture matching based approach is proposed. A global reference texture map is previously generated and stored in the system and the small local texture map is built from the captured image frame. A robust version of ICP(Iterative Closest Point)[7] matching algorithm is applied to register the local map with the global map to obtain the pose of the vehicle. The odometry data is used to obtain the prior estimation of the vehicle pose to reduce the search area in the global map and address the local minimum problem in ICP. UKF (Unscented Kalman Filter)[13] is also utilized to get more accurate result.

The rest of the paper is organized as follow: section 2 firstly discusses the system briefly; then section 3 describes the localization algorithm in detail, including ICP based map matching and UKF data fusion; next, section 4 shows the experimental results with both synthetic and real data and gives some comparisons between UKF and EKF methods; finally, section 5 ends this paper with some conclusions.

II. System introduction

A. Special Camera Configuration

The change of environmental condition, especially the change of illumination is a major problem in using vision based approach. To improve the reliability of the system, the

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camera is fixed on the bottom of the vehicle, as illustrated in Fig.1. Thus the camera has a field of view only containing the ground area right under the vehicle, and will not be affected by the light condition of the environment because almost all environmental light is shadowed by the vehicle body at that field of view. Some controllable light sources are also fixed on the bottom of the vehicle to provide a desirable light condition, which could help improve the robustness and flexibility of the system. Thanks to the special configuration, intelligent vehicles can be operated not only in the daytime with glaring sunlight but also at night.

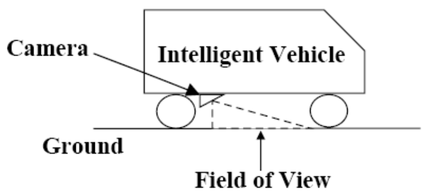

Fig.1. Special Camera Configuration

B. Vehicle Model

Let X(x,y,θ) express the vehicle pose. (x,y) and θ represent the position and direction of the vehicle in the global coordinate system, as shown in Fig.2.

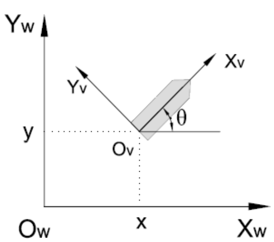

Fig.2. Vehicle Pose

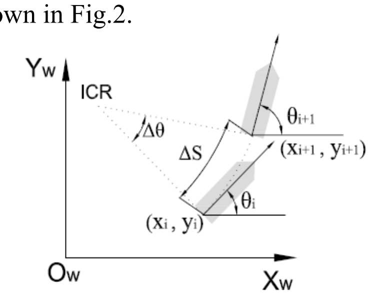

Fig.3. Vehicle Motion

Fig.3 illustrates the relationship between vehicle's pose at time step i and time step i+1. The model can be derived as (see [8] for more details):

$$\begin{bmatrix} x_{i+1} \\ y_{i+1} \\ \theta_{i+1} \end{bmatrix} = \begin{bmatrix} x_i + \Delta S \cdot \cos(\theta_i + \Delta\theta/2) \\ y_i + \Delta S \cdot \sin(\theta_i + \Delta\theta/2) \\ \theta_i + \Delta\theta \end{bmatrix} \quad (1)$$

where (ΔS , $\Delta\theta$) represents the odometry data, which can be gained from the optical encodes fixed on the vehicle.

C. Environment Model

As the camera just captures the image of the ground where the vehicle moves, the environment can be simplified to 2-D ground. There are some methods to model the environment, including grid modeling[9]10], feature based modeling[11] and topological modeling[12]. The grid based model is utilized in our approach.

The environment is focused on the urban areas, such as public park, plaza, campus and road crossing. These places possess abundant texture information in the ground, such as squares, triangles, circles, arrows or other kinds of patterns. The texture information which can be used as feature in the ground is added to the grid modeling map.

In order to make our approach be available for ground with all kinds of texture, the edge points of texture are used and represented as feature information in the map. To describe the global reference texture map, the ground is divided into small identical grids and every one covers an area of 1cm×1cm. Every grid has a value of "1" or "0", which represents it covers the edge point(s) of texture or not.

III. LOCALIZATION ALGORITHM

Global localization is achieved by map matching using a robust version of ICP algorithm. In addition, odometry data and UKF are utilized to address the local minimum problem in ICP and to improve the accuracy. The block diagram of the whole algorithm is shown in Fig.4.

A. Texture Extraction

The current frame captured by the camera is about a small ground area right under the vehicle. The aim of texture extraction is to obtain the texture's edge points from the current frame to build a small local map. The main steps are shown below:

a).Obtain the odd field image from current frame. Considering the delay in the frame capturing, the odd field image instead of the whole frame is used.

b).The median filter and canny operator are utilized to reduce the noise in the image and to extract the edge points.

c). For any acquired texture(edge) point, its coordinates in the vehicle coordinates is computed by homography transform between the image plane and the ground plane, which can be determined in previous camera calibration.

Then a local map can be generated, which represents the texture information of a small ground area right under the vehicle.

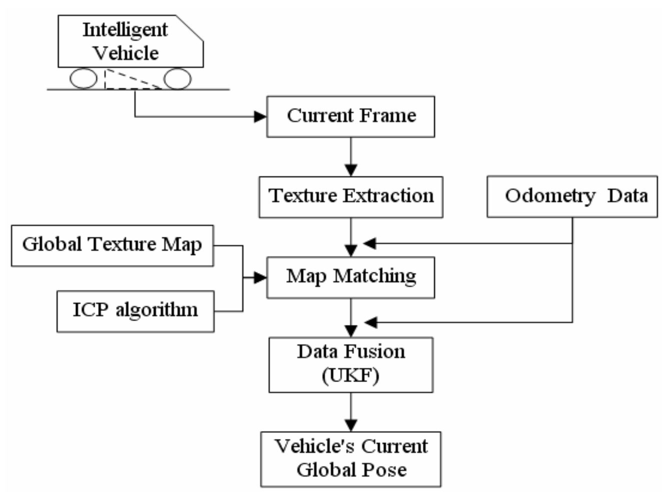

Fig.4. Localization Algorithm

B. ICP based Map Matching

A global reference grid map with texture information is previously generated and stored in the system. Global localization can be achieved by matching the local map with the global one. A robust matching algorithm should be used to insure the reliability.

Considering that the local map and global map are both composed of texture edge points, so the map matching can be viewed as a two point-sets matching, which are related by a rotation and a translation. The ICP algorithm[7] is a useful method to solve this kind of problems. ICP selects the closest point as the corresponding point and estimates the matching result by minimizing the value of a given error function. These two steps are iteratively implemented to obtain high accuracy. Every edge point in the local map searches its corresponding point in the global map.

A challenge in the ICP is how to reduce the search area in the global map. Large search area will increase the computation considerably and make the result get into local minimum. Here, odometry data is utilized to address this problem. According to equation(1), the prior estimation of vehicle pose can be obtained and we can search in a small area just around the estimated pose. The size of the area is relevant to the uncertainty of odometry data.

In order to improve the robustness, M-estimator is added to the classic ICP algorithm. Given h pairs of corresponding points $\{(P_i, CP_i)\}, i = 1 \cdots h$. The error function of ICP is defined in the form of weighted least-square:

$$E_d(r,T) = \frac{1}{h}\sum_{i=1}^{h}\lambda_i \cdot (R_r \cdot P_i + T - CP_i)^2 \tag{2}$$

where:

$$R_r = \begin{bmatrix} \cos(r) & -\sin(r) \\ \sin(r) & \cos(r) \end{bmatrix}$$

$$T = \left[t_x, t_y\right]^T \quad P_i = \left[x_i, y_i\right]^T \quad CP_i = \left[cx_i, cy_i\right]^T$$

λ_i is weight coefficient, defined as:

$$\lambda_i = \begin{cases} 1, & |e_i| \le \mu + \sigma \\ \sigma / |e_i|, & \mu + \sigma < |e_i| \le \mu + 3\sigma \\ 0, & \mu + 3\sigma < |e_i| \end{cases}$$

where $|e_i|$ is the absolute value of residual error, μ is the mean of $|e_i|$, σ is the standard variance of $|e_i|$.

A closed-form solution can be derived as:

$$r = \tan^{-1}\frac{\sum_{i=1}^{h}\lambda_i \cdot \left[(x_i - \overline{x})(cy_i - \overline{cy}) - (y_i - \overline{y})(cx_i - \overline{cx})\right]}{\sum_{i=1}^{h}\lambda_i \cdot \left[(x_i - \overline{x})(cx_i - \overline{cx}) + (y_i - \overline{y})(cy_i - \overline{cy})\right]}$$

$$\begin{cases} t_x = \overline{cx} - (\overline{x} \cdot \cos(r) - \overline{y} \cdot \sin(r)) \\ t_y = \overline{cy} - (\overline{x} \cdot \sin(r) + \overline{y} \cdot \cos(r)) \end{cases}$$

where:

$$\overline{cx} = \frac{\sum_{i=1}^{h}\lambda_i \cdot cx_i}{\sum_{i=1}^{h}\lambda_i} \quad \overline{cy} = \frac{\sum_{i=1}^{h}\lambda_i \cdot cy_i}{\sum_{i=1}^{h}\lambda_i} \quad \overline{x} = \frac{\sum_{i=1}^{h}\lambda_i \cdot x_i}{\sum_{i=1}^{h}\lambda_i} \quad \overline{y} = \frac{\sum_{i=1}^{h}\lambda_i \cdot y_i}{\sum_{i=1}^{h}\lambda_i}$$

(r, t_x, t_y) is the matching result, which represents the rotation and translation between the local map and the corresponding submap in the global reference map. This result can be used to localize the intelligent vehicle.

Let (X_V, θ) express the current vehicle pose obtained by equation(1). Let P represent a texture edge point in the local map. Its global and local coordinates (i.e.vehicle coordinates) are represented by X_W and X_L. Let CP be the corresponding point of P in the global map. Its global and local coordinates are represented by CX_W and CX_L. Because the ICP algorithm is carried out in the local coordinate system, we can obtain the following equations:

$$CX_L = R_r \cdot X_L + T \tag{3}$$

$$\begin{aligned} CX_W &= R_\theta \cdot CX_L + X_V \\ &= R_\theta \cdot R_r \cdot X_L + R_\theta \cdot T + X_V \\ &= R_{\theta+r} \cdot X_L + R_\theta \cdot T + X_V \end{aligned} \tag{4}$$

where : $R_\theta = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix}$

The corrected vehicle pose can be derived as:

$$\begin{cases} X_V^* = R_\theta \cdot T + X_V \\ \theta^* = \theta + r \end{cases} \tag{5}$$

C. UKF Data Fusion

Although the equation(5) can be considered as the final result for obtaining the vehicle pose, the ICP based map matching inevitably contains some errors. In order to get higher accuracy, the map matching result is fused by odometry data using UKF method[13][14].

UKF is a nonlinear estimation algorithm, which utilizes a deterministic "sampling" approach to calculate the mean and covariance of the state. The state distribution approximated by Gaussian random variables is represented by a set of chosen sample points. These sample points capture the true mean and covariance of the state distribution, and when propagated through the nonlinear system, capture the posterior mean and covariance.

The basic framework for UKF involves estimation of the state of a discrete-time nonlinear dynamic system, shown as below[15]:

$$X_{k+1} = F(X_k, U_k) + w_k$$

$$Z_{k+1} = H(X_{k+1}) + v_{k+1}$$

where X_k represents the state of the system(here, the vehicle pose); U_k is the known external input; Z_k is the observed measurement. The process noise and measurement noise are given by w_k and v_k and assumed zero mean additive noise with Gaussian distribution. The system's dynamic model F and H are defined as:

$$X_{k+1} = \begin{bmatrix} x_{k+1} \\ y_{k+1} \\ \theta_{k+1} \end{bmatrix} = \begin{bmatrix} x_k + \Delta S_k \cdot \cos(\theta_k + \Delta\theta_k / 2) \\ y_k + \Delta S_k \cdot \sin(\theta_k + \Delta\theta_k / 2) \\ \theta_k + \Delta\theta_k \end{bmatrix} + \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} \tag{6}$$

$$Z_{k+1} = \begin{bmatrix} x_{k+1} \\ y_{k+1} \\ \theta_{k+1} \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} \tag{7}$$

The equation(6) is derived from equation(1).The observed measurement Z_{k+1} is given directly by the vehicle pose containing measurement noise, which is depicted in equation (7). UKF involves the recursive estimation of the mean and covariance of the state and the procedure is given below[15].

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1) Initialize with:

$$\bar{X}_0 = E(X_0)$$
$$P_{xx,0} = E[(X_0 - \bar{X}_0)(X_0 - \bar{X}_0)^T]$$

For k =1 … ∞

2) Calculate sample points:

$$\chi_k = [\bar{X}_k \quad \bar{X}_k + \sqrt{(n+\lambda)P_{xx,k}} \quad \bar{X}_k - \sqrt{(n+\lambda)P_{xx,k}}\ ]$$

3) State prediction equations:

$$\chi_{k+1}^- = F(\chi_k, U_k)$$
$$\bar{X}_{k+1}^- = \sum_{i=1}^{2n+1} w_i^m \chi_{k+1,i}^-$$
$$P_{xx,k+1}^- = \sum_{i=1}^{2n+1} w_i^c (\chi_{k+1,i}^- - \bar{X}_{k+1}^-)(\chi_{k+1,i}^- - \bar{X}_{k+1}^-)^T + Q$$

4) Recalculate sample points:

$$\chi_{k+1}^* = [\bar{X}_{k+1}^- \quad \bar{X}_{k+1}^- + \sqrt{(n+\lambda)P_{xx,k+1}^-} \quad \bar{X}_{k+1}^- - \sqrt{(n+\lambda)P_{xx,k+1}^-}\ ]$$

5) Measurement update equations:

$$Z_{k+1}^- = H(\chi_{k+1}^*)$$
$$\bar{Z}_{k+1}^- = \sum_{i=1}^{2n+1} w_i^m Z_{k+1,i}^-$$
$$P_{zz,k+1}^- = \sum_{i=1}^{2n+1} w_i^c (Z_{k+1,i}^- - \bar{Z}_{k+1}^-)(Z_{k+1,i}^- - \bar{Z}_{k+1}^-)^T + R$$

6) State update equations:

$$P_{xz,k+1} = \sum_{i=1}^{2n+1} w_i^c (\chi_{k+1,i}^* - \bar{X}_{k+1}^-)(Z_{k+1,i}^- - \bar{Z}_{k+1}^-)^T$$
$$K_{k+1} = P_{xz,k+1} P_{zz,k+1}^{-1}$$
$$\bar{X}_{k+1} = \bar{X}_{k+1}^- + K_{k+1}(Z_{k+1}^* - \bar{Z}_{k+1}^-)$$
$$P_{xx,k+1} = P_{xx,k+1}^- - K_{k+1} P_{zz,k+1} K_{k+1}^T$$

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where n is the dimension of the state; $\lambda = a^2(n+s) - n$ is a scaling parameter, a determining the spread of the sample points around $\bar{X}_k$, s used as a secondary scaling parameter which is often set to 0 or 3-n; $\bar{X}_k + \sqrt{(n+\lambda)P_{xx,k}}$ means the linear algebra operation of adding a column vector $\bar{X}_k$ to each column of the matrix's square root $\sqrt{(n+\lambda)P_{xx,k}}$; Q and R is the process noise covariance and measurement noise covariance which can be estimated by the uncertainty of odometry data and the uncertainty of ICP based map matching. Z_{k+1}^* obtained from equation(5) represents the vehicle pose by ICP based map matching. w_i is the sample weights, defined as:

$$w_1^m = \lambda/(n+\lambda)$$
$$w_1^c = \lambda/(n+\lambda) + (1 - a^2 + b)$$
$$w_i^m = w_i^c = 1/[2(n+\lambda)] \qquad i = 2, \cdots, 2n+1$$

where b is used to incorporate prior knowledge of the state distribution(for Gaussian distribution, b=2 is optimal).

IV. Experiments

A. Experiments with Synthetic Data

A vision simulation system was developed to generate virtual vehicle pose information and vision data by a virtual camera fixed on the vehicle. The vehicle can be controlled through keyboard. Fig.5 shows the virtual ground in the synthetic environment, which contains complex random texture.

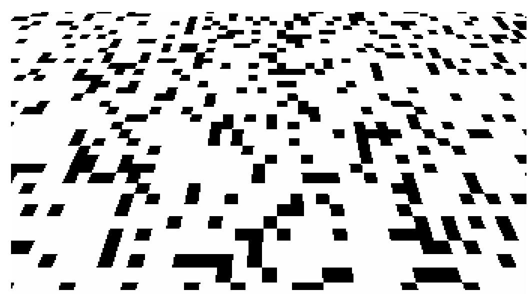


Fig.5. Virtual Ground

In the experiment, the vehicle was moving along a circle with a diameter about 45 meters. In order to make the synthetic experiment more similar to the real one, the virtual odometry data was generated by adding Gaussian noise. The UKF parameters are set as follow: n is set to 3 (dimension of the state), a is set to 0.25, s is set to 0 and b is set to 2.

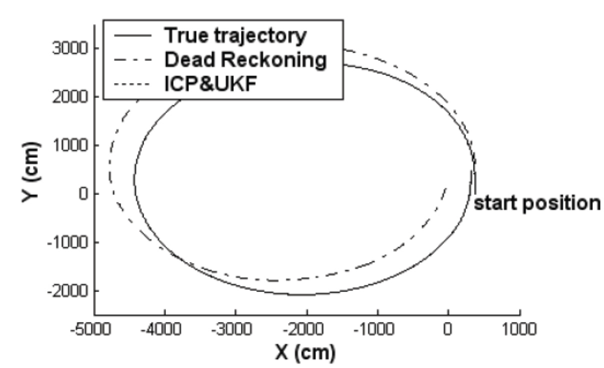
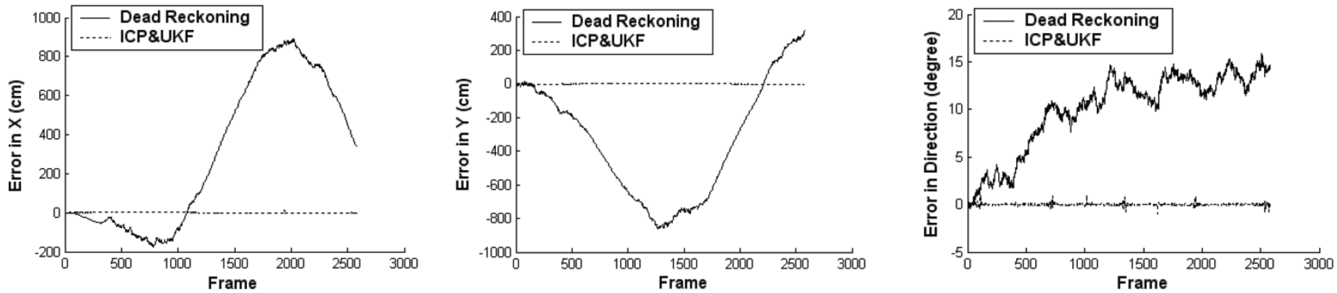


Fig.6. Result with Synthetic Data



(a) (b) (c)

Fig.7. Errors with Different Methods

Fig.6 shows the trajectories by different methods. Although the large cumulative error over time is unavoidable by using dead reckoning, the trajectory by proposed approach(called ICP&UKF) is very close to the true trajectory. Fig.7 illustrates the error analysis results which also demonstrate the high accuracy of the proposed approach.

Some results of other approaches are shown in Tab.1. Comparison shows that the ICP&UKF method is more accurate than ICP&EKF (the ICP based map matching result and odometry data are fused by Extended Kalman Filter), which indicates the better performance of UKF than EKF. It is surprising that the ICP based map matching without data fusion method has the best result. That is mainly because of two reasons. First, in the ideal synthetic environment, the reliable and accurate texture extraction makes the ICP algorithm highly accurate. Second, the parameters in the data fusion methods, especially the estimated process noise covariance and measurement noise covariance are not optimal.

Tab.1. Error Comparisons among Different Approaches

Approaches / Vehicle pose		ICP	ICP&EKF	ICP&UKF
x (cm)	mean	1.52	1.56	1.52
	std	0.85	0.95	0.89
y (cm)	mean	1.60	1.67	1.60
	std	0.81	0.89	0.86
θ (degree)	mean	0.055	0.141	0.056
	std	0.084	0.086	0.084

*the mean and std represent the mean and standard deviation of error to the true vehicle pose.
*ICP represents the ICP based map matching approach.

B. Experiments with Real Data

The proposed approach has been tested with real data from the intelligent vehicle developed at Shanghai Jiao Tong University, as shown in Fig.8. The vision data is captured by a Logitech web camera, which is fixed on the bottom of the vehicle aiming at reducing the affection of environment disturbances. The experimental place is in the campus, as shown in Fig.9, which contains abundant square textures in the ground. The global reference texture map is previously generated and stored in the system.

In the first experiment, the vehicle was moving along a circle with a diameter about 15 meters. Fig.10 shows the trajectories by different methods. The true trajectory was drawn on the ground by a pen fixed on the vehicle. Compared with the result by dead reckoning which shows large accumulative errors over time, the trajectory by the map matching method is more accurate and closer to the true trajectory. However, the result by map matching is not smooth enough, which due to the errors in the texture extraction and ICP algorithm.

Fig.8. Intelligent Vehicle Fig.9. Real Experimental Environment

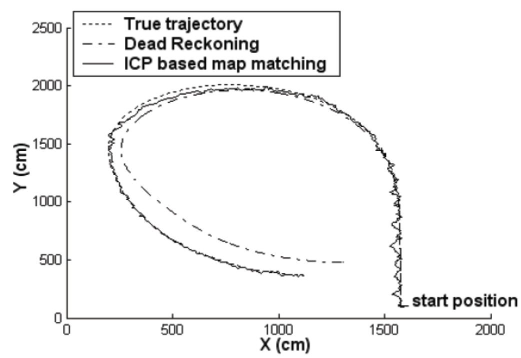


Fig.10. Result with Real Data (1)

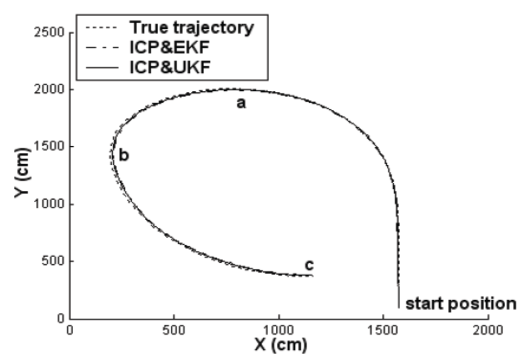
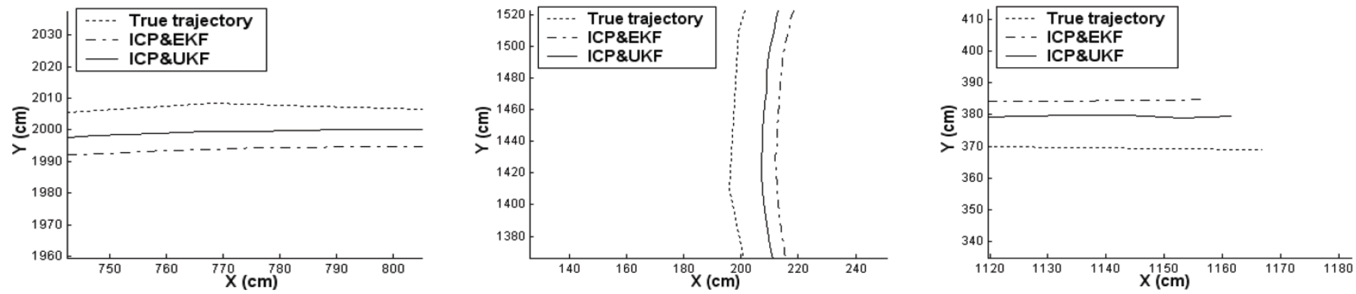


Fig.11. Result with Real Data (2)



(a) Zoomed-in Figure at a in Fig.11 (b) Zoomed-in Figure at b in Fig.11 (c) Zoomed-in Figure at c in Fig.11

Fig.12. Zoomed-in Figures in Fig.11

The second experiment was implemented to show the effectiveness of data fusion methods. Compared with the result by ICP based map matching in Fig.10, the result in Fig.11 is smoother and more accurate, which shows the good performance of fusion methods. Fig.12 shows the zoomed-in figures at a, b and c in Fig.11, which proves again that UKF provides superior performance than EKF. With an equivalent computational complexity with EKF, UKF can be an ideal approach in the application areas of nonlinear estimation in which the EKF has been applied.

V. CONCLUSION

In order not only to solve the global localization problem for intelligent vehicles but also to improve the reliability of the vision based system in urban environment, a special camera configuration and a map matching based approach are proposed. ICP algorithm with M-estimator is applied to solve the matching problem. The prior estimation of the vehicle pose by odometry data to reduce the search area in the global map successfully addresses the local minimum problem and high computation problem with the ICP algorithm. Map matching result is then fused with odometry data by UKF method to obtain high accuracy. Experimental results with both synthetic and real data prove the high accuracy and reliability of the proposed approach. Since generally there is abundant texture information in the ground in urban areas, such as public park, plaza and road crossing, the proposed approach has practical application value.

The ground with square texture was selected to carry out the experiments with real data because of the easy generation of the global reference texture map. In order to implement the proposed approach in other environments with different kinds of texture, future work will focus on automated global map building, in which RTK-GPS can be used as an assistant. Vision based SLAM(simultaneously localization and map building) is also an emphasis in our future work.

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