# Underwater Vehicle Motion Parameters Estimation Simulation and Experiment Based on Monocular Vision and Low Cost Inertial Measurement Unit

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## ABSTRACT

In this paper, authors proposed a practical motion estimation strategy to obtain the single static object position and the vehicle's motion parameters simultaneously by utilizing camera and IMU (Inertial Measurement Unit), and tried several classic nonlinear parameters estimation methods on this problem based on the Matlab simulation. A lot of preliminary calibration experiments have been done to fuse the data from IMU and camera, which included: camera calibration, IMU error modeling, and relative attitude calibration between IMU and camera. The obtaining of sensor's model made the simulation work be possible, and the PF algorithm can track the vehicle's motion parameters and obtain the target position very well. The accuracy is centimeter level.

KEY WORDS: I-AUV; camera and IMU; nonlinear parameter estimation; particle filter; relative calibration; data fusion.

## INTRODUCTION

IAUV(Intervention-Autonomous Underwater Vehicle) is a kind of special underwater vehicle which can perform the tasks autonomously, such as installing instruments on the sea floor, searching, locating, approaching and docking on the underwater device; retrieving geological/biological sampling etc (Wang,1996). Currently such tasks mostly are performed by ROV (Remotely Operated Vehicles), and only few intervention missions have be performed in the real sea environment by IAUV(Marani,Choi and Yuh,2009). In order to perform the underwater intervention missions, imaging sonar, ultra-low-light camera, Inertial Navigation System, Long Base Line System, doppler sonar need to be fixed on the vehicle(Evans and Redmond, 2003), and the general intervention mission can be performed following the six stages process. 1) Launching from R/V ship. 2) Searching and navigating to the worksite( $\infty$ m- 25m). In this stage, sonars (image sonar, multibeam sonar or sidescan sonar) are used to search the suspected targets, navigation sensors (LBL(Long Base Line), doppler sonar, INS(Inertial Navigation System), image sonar and high precision camera(Stefan and Ian, 2004) ) are used to track the vehicle's position and attitude. 3) Approaching the target(25m-2m). In this stage image sonar or dual-frequency identification sonar can be used to identify the true target. 4) Localizing the position of target (<2m). The sensor usually used in this stage is cameras. 5) Accurately docking, retrieving the sample or installing instrument by the manipulator mounted on the vehicle.6)The task is finished, and the IAUV can continue moving to another suspected target or return to the recovery point. The research in this paper is focused in the fourth stage. The employed strategy is obtaining the position of target and optimal estimation of the motion parameters of IAUV (position, attitude, velocity, angle rate and acceleration) simultaneously. The sensors used in the strategy are single camera and low-cost IMU. A new IAUV testbed project is underway in Shenyang Institute of Automation, C.A.S, in which the research is focused on the stage 4 and 5(Zhang, 2007).

Fig. 1 IAUV testbed

The remainder of this paper is organized as follows. In problem statement section, the target perception strategy, principle and research challenges are proposed. In sensor modeling section, the calibration of camera, IMU error modeling and relative attitude calibration between camera and IMU are described. It's the foundation to continue the simulation of estimation problem. In estimation algorithm section, the classic EKF, UKF and PF are introduced. In the last section, the simulation and experiments are stated about sensor's modeling and estimation results.

## PROBLEM STATEMENT

It's clearly that it's impossible for human to feel the distance between them and one target in front of them with one eye. It's the same with the robot vision. At least two cameras are needed to obtain the distance information by observing the same target simultaneously. Another

Paper No. ISOPE-2009-_305_ First author's last (family) name _Li_ Total number of pages _8_
Supported by "863" Program (2006AA09Z217).
Supported by the Knowledge Innovation Program of Chinese Academy of Sciences (07A6050601).

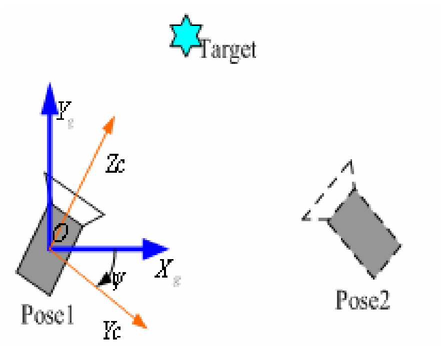


Fig. 2 localization principle based on monocular vision

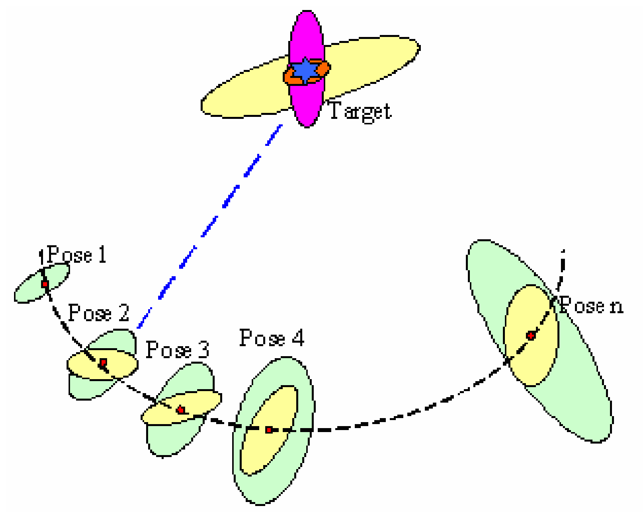


Fig. 3 camera trajectory and its pose uncertainty

method solving the problem is to observe the same target at different positions with single camera. The principle is shown in Fig. 2 $Y_cOZ_c$ is the horizontal plane in camera frame and $X_gOY_g$ is the horizontal plane in global frame. In this paper, camera is mounted on the IAUV, a superior arc is selected to move vehicle from one observing point to another one. The advantages of the trajectory are: 1) the camera view field is small and such trajectory can keep the target in the view field more easily.2) there is enough time to make the estimation algorithm convergence. If the accurate position and attitude of the camera is known, the target's position can be obtained in the global reference frame with the method of triangulation. However, although the principle of localizing the target is easy, it is not easy to obtain the accurate pose (position and attitude) of the camera. The reason is described as follows. Theoretically the pose of camera can be calculated iteratively by integrating acceleration twice and integrating angular rate once when the initial Euler angle and initial position are known. However, low cost IMU can only provide us the line acceleration and angle rate information of the camera which includes the acceleration of gravity and the unbounded drift error. The acceleration of gravity will introduce the unexpected acceleration error on the three frame axis direction if no accurate camera attitude is provided. The drift error also makes the pose error be more uncertainty. This can be shown in Fig. 3. The camera's moving trajectory and pose uncertainty is shown. The red points represent the ideal position of the camera, and the green ellipse means the uncertainty of camera's position in horizontal plane. It can be seen that the uncertainty increases with the time passing. If such pose are used to localize the

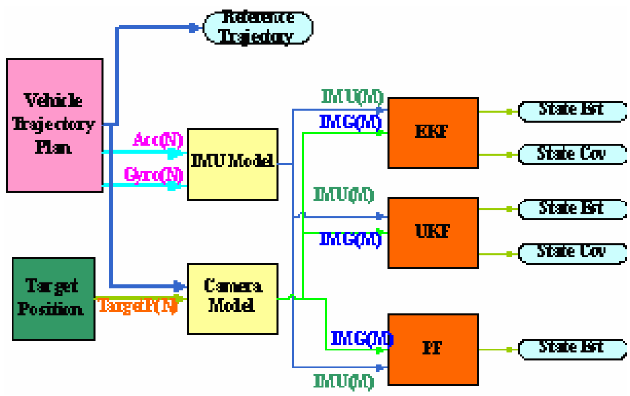


Fig. 4 parameters estimation flow chart

position of target, it must be inaccurate.

In order to cope with the pose inaccuracy of camera, it's sensible to use another sensor to calibrate the pose uncertainty. Fortunately, the camera is a good one to provide redundant information to decrease its pose uncertainty. In Fig.3, the blue dashed line represents that the camera is observing the target object. With the two complementary sensors' information and proper estimation algorithm, the target position and the vehicle[1]'s pose can be obtained simultaneously. The estimation result will be used to realize the docking and sampling (Li, Zhang and Wang, 2008) at the next stage of the intervention mission.

Fusing IMU and monocular vision to estimate the target position and the vehicle's pose presents several challenges to the optimal estimation algorithm. 1) In the system only the target orientation can be observed and the distance information is lost. 2) The strong nonlinear character of state equation and measurement equation. 3) The initial target position is unknown. Many researchers used the UKF (Unscented Kalman Filter) to obtain the optimal estimation (Andreas, 2003; Jacob, 2006). However, in this special problem the UKF can not estimate the true pose of vehicle and target. Thus in my simulation, another nonlinear parameter estimation method—PF(Particle Filter) is tested in matlab environment.

In Fig. 4, the parameters estimation flow chart is shown. Vehicle moves along a 120 degree superior arc and the target locates in the circle center of the trajectory. The theoretical value of acceleration and gyro are input IMU model and camera model in order to emulate the acceleration and gyro measurement value from low-cost IMU. The two models are described in the sensor modeling section.

## SENSORS MODELING

### Camera Calibration

In robot vision community, the purpose of camera calibration is obtaining the internal parameters and external parameters of the camera. In many cases, the robot vision system depended on the calibration accuracy of camera strongly (Tsai and Lens, 1989).

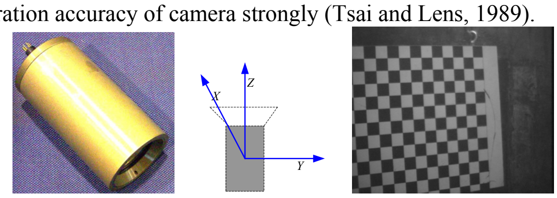


Fig. 5 (a)underwater camera,(b) coordinate frame(c) gridiron pattern

[1] The camera is mounted on the vehicle rigidly.

There are many standard calibration methods currently. In this paper, four steps calibration method proposed by Heikkia (Heikkila and Silven, 1996) is adopted. The method is very simple and it needs only a calibration reference, eg. gridiron pattern. According to formula of the camera model, the position of corner point in the image plane can be calculated. At the same time the corresponding position in the image plane can be measured. Thus the least-squares internal parameters estimation can be obtained. The target position in image plane is calculated according to the target position in camera frame and the internal parameters which have been obtained by calibration (Li, 2008). The measurement model can be written as

$$u = \alpha_x \frac{S_x}{S_z} + u_0 + w_{cy} \tag{1}$$

$$v = \alpha_y \frac{S_y}{S_z} + v_0 + w_{cz} \tag{2}$$

$$\alpha_x = f / dx, \alpha_y - f / dy \tag{3}$$

where $f$ is the camera focal distance, $dx$, $dy$ are the length of 1 pixel in image plane. $(S_x, S_y, S_z)$ are the target position in camera coordinate frame. $(u, v)$ are the target position in image plane. $(u_0, v_0)$ are the principle point position in image plane. $w_{cx}$ , $w_{cy}$ are zero mean white Gaussian noise.

$\begin{bmatrix} \alpha_x & 0 & u_0 & 0 \\ 0 & \alpha_y & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$ is the internal parameters of camera.

## IMU Error Model

The general error model of IMU can be expressed as

$$b(t) = b0 + b1(t) + bw(t) \tag{4}$$

where *b(t)* is the error of IMU, *b0* is constant error, *bw(t)* can be thought as band-limited white noise, *b1(t)* is time-variant error bias. b0 can be obtained/eliminated by three methods. 1) high pass filtering, 2)off-line calculation, 3)online estimation. In this paper, online estimation is adopted because of the drawback of method 1 and method 2. (Li, 2008) The model of *b1(t)* is complex, and the Allan variance is an important factor for the model of this variable(Walter, 2001).

Thus, the IMU model can be written as

$$x_m = x_t + x_0 + \dot{x}_b + x_w \tag{5}$$

where *m* means measurement value(acceleration/gyro), t means the true value, *0* means constant error, *w* means the white Gaussian noise, $\dot{x}_b$ means that the time-variant *b1(t)* can be modeled as rate random walking model.

## Relative Attitude Calibration between IMU and Camera

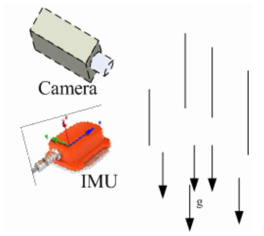


Fig. 6 calibration principle

In Fig. 6, relative attitude calibration principle is shown. It needs IMU and camera measure the direction of gravity simultaneously. IMU can measure it by the acceleration value, and camera can measure it by observing gridiron pattern to obtain the vanish point of two parallel lines.

ESTIMATION ALGORITHM

## Definition of Coordinate Frame

***Global Coordinate Frame***

The origin locates at buoyant center of vehicle at the vehicle's initial position. The direction is North-East-Down.

***IMU Coordinate Frame***

The origin locates at gravity center of IMU. The direction is North-East-Down.

***Camera Coordinate Frame***

The origin locates at the optical center of camera. The optical axis is Z axis. The Y axis directs the right of the camera, and X axis can be defined by using right-hand rule.

## State Equation

A general discrete state equation can be described as

$$x_{k+1} = \Phi_{k+1,k} * x_k + \Gamma_k * w_k \tag{6}$$

Here, the kinematics equation of the vehicle and IMU error model are used as the state equation. The state variable is $(X, Y, Z, \phi, \theta, \psi, u, v, w)$ --position, attitude, linear velocity; $(b_{ax}, b_{ay}, b_{az}, b_{ax0}, b_{ay0}, b_{az0}, b_p, b_q, b_r, b_{p0}, b_{q0}, b_{r0})$ -- time-variant error bias and constant error of IMU; $(X_0, Y_0, Z_0)$ -- target position. The state equation can be written as

$$\dot{X} = \cos\psi \cos\theta u + (\cos\psi \sin\theta \sin\phi - \sin\psi \cos\phi) v + (\cos\psi \sin\theta \cos\phi + \sin\psi \sin\phi) w \tag{7}$$

$$\dot{Y} = \sin\psi \cos\theta u + (\sin\psi \sin\theta \sin\phi + \cos\psi \cos\phi) v + (\sin\psi \sin\theta \cos\phi - \cos\psi \sin\phi) w \tag{8}$$

$$\dot{Z} = -\sin\theta u + \cos\theta \sin\phi v + \cos\theta \cos\phi w - \tan\theta \cos\phi (z_r - b_r - b_{r0}) + w1 \tag{9}$$

$$\dot{\phi} = (z_p - b_p - b_{p0}) + \tan\theta \sin\phi (z_q - b_q - b_{q0}) \tag{10}$$

$$\dot{\theta} = \cos\phi (z_q - b_q - b_{q0}) - \sin\phi (z_r - b_r - b_{r0}) + w2 \tag{11}$$

$$\dot{\psi} = \frac{\sin\phi}{\cos\theta}(z_q - b_q - b_{q0}) + \frac{\cos\phi}{\cos\theta}(z_r - b_r - b_{r0}) + w3 \tag{12}$$

$$\dot{u} = z_x - b_{ax} - b_{ax0} - n_{ax} \tag{13}$$

$$\dot{v} = z_y - b_{ay} - b_{ay0} - n_{ay} \tag{14}$$

$$\dot{w} = z_z - b_{az} - b_{az0} - n_{az} \tag{15}$$

$$\dot{b}_{ax} = -1/\tau_{ax} * b_{ax} + n_{axw} \tag{16}$$

$$\dot{b}_{ay} = -1/\tau_{ay} * b_{ay} + n_{ayw} \tag{17}$$

$$\dot{b}_{az} = -1/\tau_{az} * b_{az} + n_{azw} \tag{18}$$

$$\dot{b}_p = -1/\tau_{px} + n_{pw} \tag{19}$$

$$\dot{b}_q = -1/\tau_{qx} + n_{qw} \tag{20}$$

$$\dot{b}_r = -1/\tau_{rx} + n_{rw} \tag{21}$$

$$\dot{X}_0 = 0 \quad (22)$$

$$\dot{Y}_0 = 0 \quad (23)$$

$$\dot{Z}_0 = 0 \quad (24)$$

$$\dot{b}_{ax0} = 0 \quad (25)$$

$$\dot{b}_{ay0} = 0 \quad (26)$$

$$\dot{b}_{az0} = 0 \quad (27)$$

$$\dot{b}_{p0} = 0 \quad (28)$$

$$\dot{b}_{q0} = 0 \quad (29)$$

$$\dot{b}_{r0} = 0 \quad (30)$$

where $(w_1, w_2, w_3)$ are the function of IMU's noise and attitude, and simplified as zero-mean white noise. $(n_{ax}, n_{ay}, n_{az})$ are the accelerometer's white noise. $(n_{axw}, n_{ayw}, n_{azw})$ are driven noise of 1st Markov process of accelerometer. $(n_{pw}, n_{qw}, n_{rw})$ are driven noise of 1st Markov process of gyro. $(z_x, z_y, z_z)$ are the measurement value of acceleration. $(z_p, z_q, z_r)$ are the measurement value of angular rate. $(\tau_{ax}, \tau_{ay}, \tau_{az}, \tau_{px}, \tau_{py}, \tau_{pz})$ are the time constant of 1st Markov process of IMU.

### Measure equation

A general discrete measurement equation is described as

$$x_{k+1} = H_{k+1} * x_{k+1} + \Lambda_{k+1} * v_{k+1} \quad (31)$$

In this paper, the camera's model serves as the measure equation. It is expressed as Eqs.1~2.
Until now, the state equation and measurement equation which are used to estimate the target position and vehicle's state simultaneously are listed.

### Nonlinear State/Parameter Estimation Algorithm

The target localization and vehicle's motion state estimation is a complex problem of nonlinear state/parameter estimation. The state equation and measure equation are strongly nonlinear. However, only target's orientation information and the vehicle's inertial information with unbounded-drift error are available. Not all nonlinear state filters are applicable. Thus three algorithms, EKF, UKF and PF, are tried on this strongly nonlinear estimation problem. The three method are representative in the nonlinear system estimation problems and can be found in (Arthur,1974;Simon,2000;Gordon,1994). The simulation results show that the PF is the only selection to solve this estimation problem.

## SIMULATION AND EXPERIMENT

### Camera Calibration

Currently, because the IAUV is under constructing, the work on camera calibration is done on land. This method will be transferred to underwater environment after IAUV can work in water.

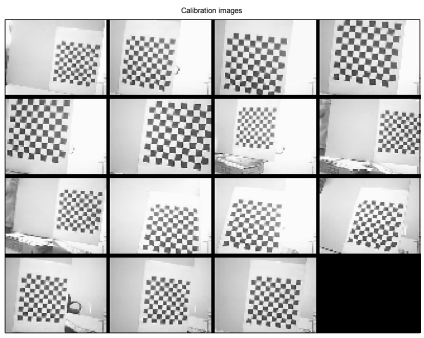


Fig. 7 pictures used to calibrate

The tools needed are a USB camera and a gridiron pattern. The calibration toolbox is based on matlab (Bouguet,2008). In Fig. 7, the pictures used to calibrate the camera are shown. By calibration, the internal parameters are obtained.
Focal Length: fc = [ 414.80945 414.01662 ] [ 4.83991 4.77519 ]
Principal point: cc = [ 139.65239 106.88530 ] [ 2.76402 2.75073 ]
Distortion: kc = [ -0.02857 -0.21081 -0.00446 -0.00748 0.00000 ] [ 0.01627 0.08474 0.00143 0.00180 0.00000 ]
Pixel error: err = [ 0.15614 0.12380 ]

The calibration results show: 1) According to the experience about the pixel error, the camera and its model can be used in estimation problem and its accuracy is acceptable. 2) If there is a long distance between the camera and the target, the little rotation of vehicle around X axis will cause a large movement of target on image plane. Take the distance—0.8m in our experiment as one example. When the camera rotates 1degree around X axis, the target will move 10 pixels, that is, 0.1mm on the image plane. In the global frame, it will move about (0.1/4) *0.8=0.02m.

### IMU Error Model

In this paper, low cost IMU- MTi is used. This sensor can provide us the acceleration, gyro and attitude. Although in the manual of MTi, the performance index is provided by the manufacturer, it is not enough for requirement of the estimation algorithm. The MTi error modeling needs to be made. These experiments include the short time calibration to observe the performance of MTi and long time calibration to obtain the error model of MTi.
***Short Time Calibration***
The results are shown in Figs.8~9.The experiment is done when the MTi is put on the plane as possible as horizontal, and the experiment time is 10 minutes. The result is shown Table 1. The result shows the output of acceleration from MTi includes gravity acceleration.

Table 1. mean value and standard error of IMU

| | AccX | AccY | AccZ |
|---|---|---|---|
| mean | 0.0051 m/s^2 | 0.0275 m/s^2 | 9.8032 m/s^2 |
| std | 0.0099 m/s^2 | 0.0116 m/s^2 | 0.0116 m/s^2 |

| | GyroX | GyroY | GyroZ |
|---|---|---|---|
| mean | -0.0087 rad/s | -0.0106 rad/s | -9.6577e-005 rad/s |
| std | 0.0067 rad/s | 0.0068 rad/s | 0.0075 rad/s |

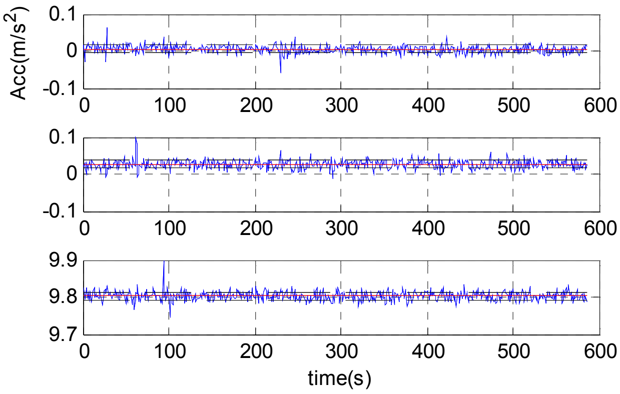


Fig. 8 linear acceleration

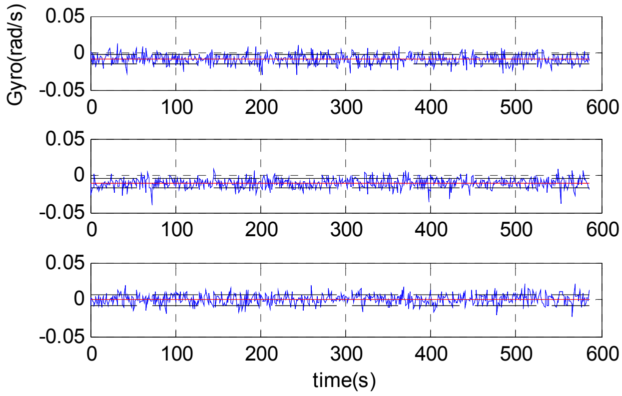


Fig. 9 angle rate

The red line is the mean of measurement and the black line is the $1\sigma$ range.

***Long Time Calibration***

The results include the recorded data over 5 hours and the Allan variance curve plotting. They are shown in Figs. 10~12.

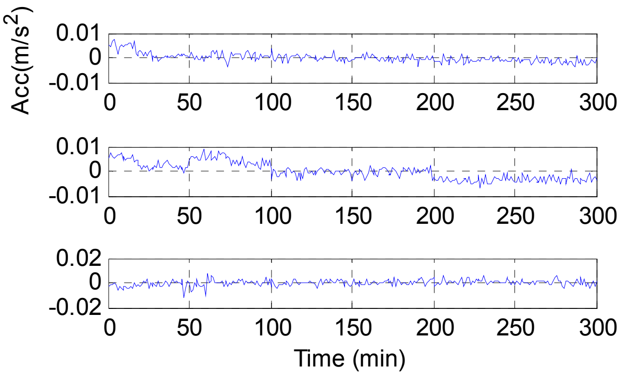


Fig. 10 acceleration value(g is eliminated)

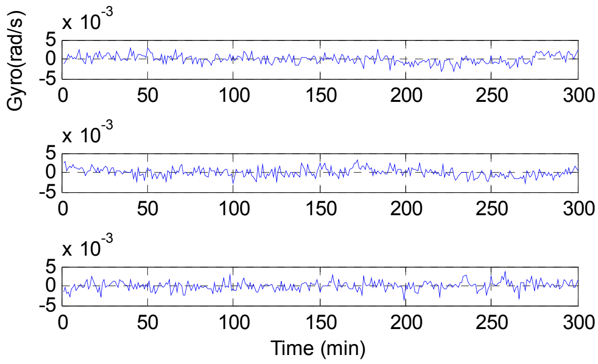


Fig. 11 angle rate

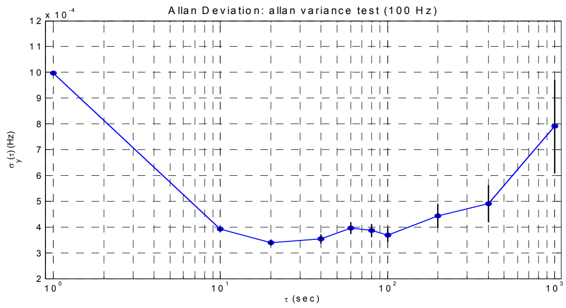


Fig. 12 (a) Allan covariance of IMU-AccX

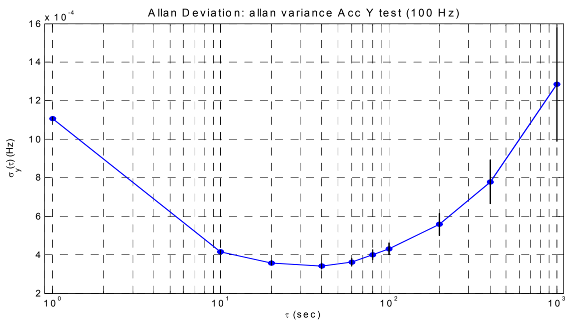


Fig. 12 (b) Allan covariance of IMU-AccY

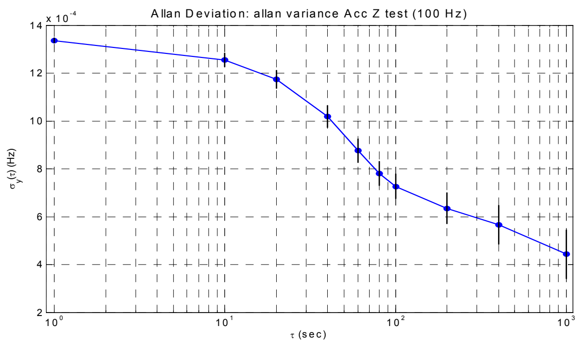


Fig. 12 (c) Allan covariance of IMU-AccZ

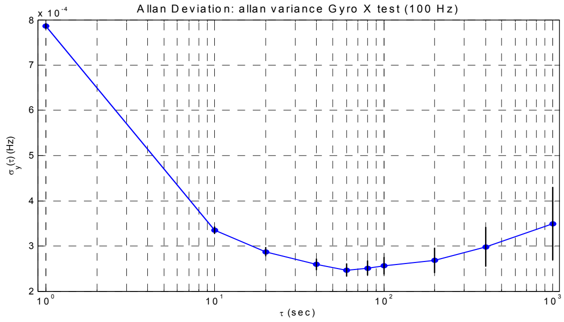


Fig. 12 (c) Allan covariance of IMU-GyroX

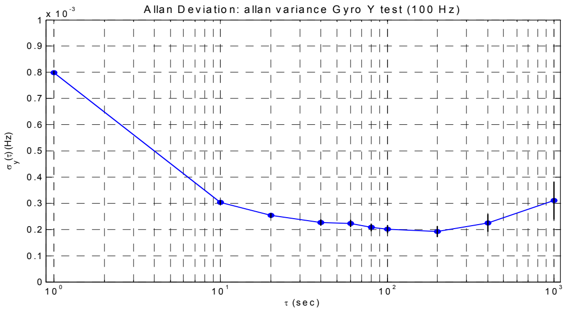


Fig. 12 (d) Allan covariance of IMU-GyroY

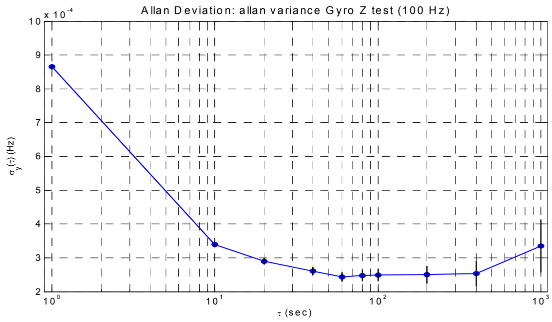


Fig. 12(e) Allan covariance of IMU--GyroZ

Table 2. IMU error model parameter

| b0 | X | Y | Z |
|---|---|---|---|
| Acc | 0.0230 m/s^2 | -0.0272 m/s^2 | 9.8066 m/s^2 |
| Gyro | -0.0088 rad/s | -0.0116 rad/s | -0.0013 rad/s |

| b1(t)_Std | X | Y | Z |
|---|---|---|---|
| Acc | 0.0086 m/s^2 | 0.0105 m/s^2 | 0.0162 m/s^2 |
| Gyro | 0.0067 rad/s | 0.0069 rad/s | 0.0076 rad/s |

| bw(t)_Std | X | Y | Z |
|---|---|---|---|
| Acc | 0.0088 m/s^2 | 0.0115 m/s^2 | 0.0159 m/s^2 |
| Gyro | 0.0067 rad/s | 0.0069 rad/s | 0.0075 rad/s |

The long time calibration result shows that the MTi error model

*Error = const error + 1$^{st}$ Markov process + white noise*

The parameters of constant error, Markov process driven noise and the white noise are shown in Table 2.

***Relative Attitude Calibration Between IMU and Camera***

Because the IAUV is under constructing, the relative calibration experiment is done on land. The experiment device is shown in Fig. 13. IMU and camera are fixed together and mounted on the end effector of the manipulator. A gridiron pattern is put in front of the camera. By this gridiron pattern, the camera can "percept" the direction of gravity in the camera frame. The MTi can calculate the gravity direction by using acceleration value in global frame.

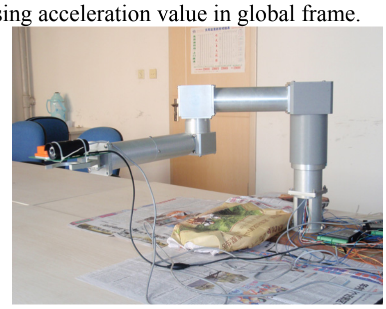

Fig.13 device of relative attitude calibration

15 frame static pictures are sampled and the output of MTi is recorded simultaneously, the relative calibration method proposed by (Jorge, L and Jorge,D, 2007) is adopted. The calibration result is

Transforming matrix description

IMU2CAM=

|  |  |  |
|---|---|---|
| 0.0401 | -0.9983 | 0.0426 |
| 0.0048 | -0.0424 | -0.9991 |
| 0.9992 | 0.0403 | 0.0031 |

which is similar to the intuitive result

$$\phi = -pi/2, \theta = 0, \psi = -pi/2$$

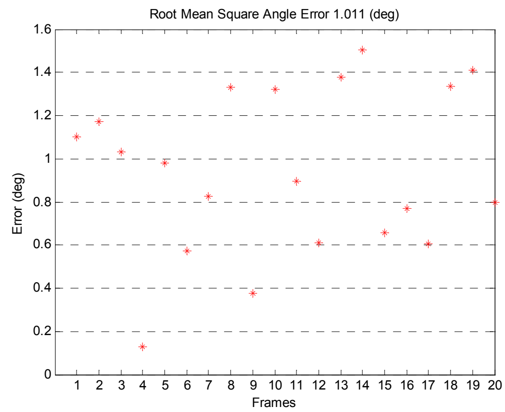


Fig. 14 standard error of relative attitude error

the standard error of relative attitude error is shown in Fig. 14. X axis is the number of picture.

## Estimation Simulation

In (Li,Zhang and Wang,2008) paper, an enough low sensors noise is assumed, and the simulation results show that EKF,UKF all estimate relative position between the vehicle and target. In this paper, however, the true sensor's noise parameters are used on the same simulator, the simulation result shows the UKF and EKF are invalid to the target localization and vehicle's motion estimation simultaneously.

In this simulation, the initial position of the vehicle is set as the origin. It rotates evenly around the target which is located in (0.866,0.5)m.

The tangential velocity of rotation is 0.1178rad/s, the simulation time is 20s and the rotation angle is 120 degree. The result from UKF and PF algorithm are shown in Fig. 15. Here the EKF results are not shown in these pictures, the estimation result of tracking the vehicle's trajectory is divergent if the EKF algorithm is performed.

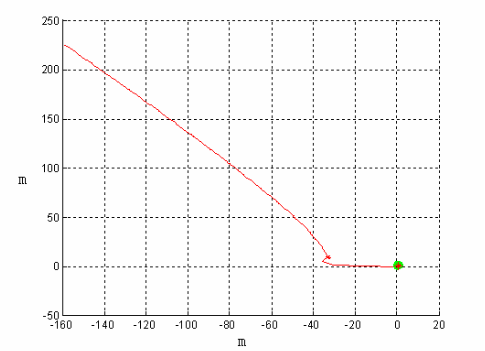


Fig. 15(a) comparison of estimation result

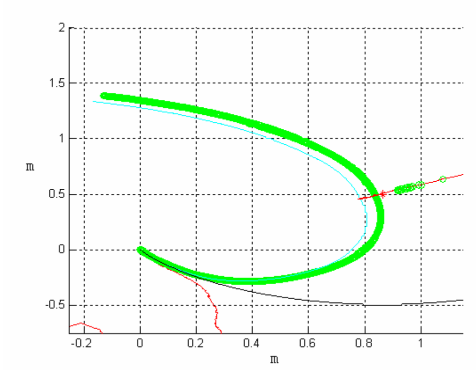


Fig. 15(b) enlarge vehicle's trajectory

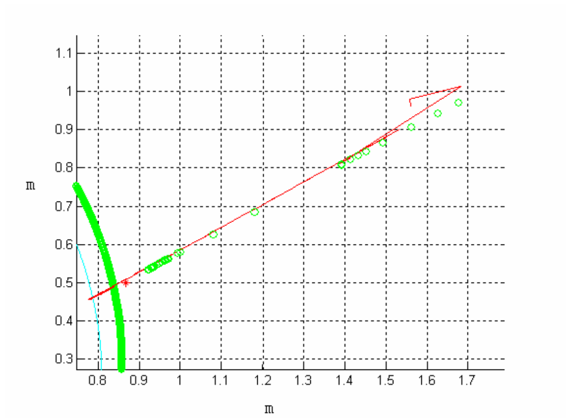


Fig.15(c) enlarge target localization

In Fig. 15(a), red line represents the position estimation of vehicle using UKF algorithm, and green line represents position estimation of the vehicle using PF. The reference trajectory can be seen in (b)--the black line. Apparently, the UKF algorithm can not track the vehicle. When the vehicle moves to the position (0.1,-0.1) m, it begins to be divergent. In (b) the blue line represents the actual trajectory because of the large noise on the vehicle. The PF algorithm tracks the actual trajectory very well. In(c), the target localization course is shown. The position estimated by PF is approaching to position (0.866,0.5) m which is the true position of target. The initial position of target is set randomly. In this simulation, it is set in the position (1.5, 1) m.

The simulation result shows that the PF algorithm can estimate the target position and track position and attitude of the vehicle simultaneously.

## CONCLUSIONS

In this paper, a strategy of target localization and vehicle motion parameters estimation simultaneously is proposed. By experimental method, we calibrate the camera and model for IMU error. Finally, variant algorithms are tried on the strongly nonlinear state estimation problem, and the simulation result shows that the PF is the best one for the problem.

## ACKNOWLEDGEMENTS

The authors wish to acknowledge the support for this work provided by the Underwater Robot Research Center, Shenyang Institute of Automation.

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