

Indoor Mobile Localization System and Stabilization of Localization Performance using Pre-filtering

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Abstract: In this paper, we present the practical application of an Unscented Kalman Filter (UKF) for an Indoor Mobile Localization System using ultrasonic sensors. It is true that many kinds of localization techniques have been researched for several years in order to contribute to the realization of a ubiquitous system; particularly, such a ubiquitous system needs a high degree of accuracy to be practical and efficient. Unfortunately, a number of localization systems for indoor space do not have sufficient accuracy to establish any special task such as precise position control of a moving target even though they require comparatively high developmental cost. Therefore, we developed an Indoor Mobile Localization System having high localization performance; specifically, the Unscented Kalman Filter is applied for improving the localization accuracy. In addition, we also present the additive filter named 'Pre-filtering' to compensate the performance of the estimation algorithm. Pre-filtering has been developed to overcome negative effects from unexpected external noise so that localization through the Unscented Kalman Filter has come to be stable. Moreover, we tried to demonstrate the performance comparison of the Unscented Kalman Filter and another estimation algorithm, such as the Unscented Particle Filter (UPF), through simulation for our system.

Keywords: Indoor GPS, Pre-filtering, Tone Detection, UKF, UPF.

1. INTRODUCTION

To obtain well-localized physical position data, many systems have addressed the problems of automatic location measurement. Because each approach solves a slightly different problem or supports different applications, they vary in many parameters, such as the physical phenomena used for location determination, the form factor of the sensing apparatus, power requirements, infrastructure versus portable elements, and resolution in time and space. Among these kinds of automatic localization systems, localizing techniques using ultrasound have been actively researched because ultrasound has a number of merits such as low cost and relative easiness of application; nevertheless, ultrasound is still

considered as a low-guaranteed sensor since it is too sensitive to be used for precise localization. Active Bat uses ultrasound in order to perform time-of-flight lateration for calculating the 3-D position of a "Bat", which can be worn on a person or object [1]. Active Bat is accurate to 9 cm; however, it requires a vast amount of infrastructure. That is, receivers need to be placed in a square grid 1.2 meters apart and connected by a network of cables. As a result, this level of infrastructure is infeasible for the system we require. In addition, Active Badge Location Systems, which consist of a cellular proximity system that use diffuse infrared technology, have difficulty in locations with fluorescent lighting or direct sunlight because of the spurious infrared emissions these light sources generate [2]. One of the representative indoor localization models is the Cricket of MIT. It is similar to Active Bat in that it uses ultrasound as a basis for time-of-flight lateration; on the other hand, it requires fewer infrastructures than Active Bat. It employs the Extended Kalman Filter (EKF) in order to enhance its localization performance. The Cricket has the position estimation accuracy of 10 cm [3,4]. Nevertheless, the Cricket is considered to be a relatively accurate localization system when compared with other localization techniques. However, it still does not have reliable accuracy of positioning for mobile objects when it comes to obtaining the position data of a dynamic target. There would be several causes that

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would detract from the otherwise outstanding performance of the Cricket; for instance, either the structural defects of hardware or the problems related to software architecture might affect the accuracy of localization. The momentous factors to cause such an unsatisfactory accuracy could be the method of approximation of EKF; because the EKF uses the first order terms of the Taylor series expansion of the nonlinear functions, it often introduces large errors in the estimated statistics of the posterior distributions of the states [5]. Moreover, although the EKF is a widely used filtering strategy, it has led to a general consensus that it is difficult to implement and to tune, and only reliable for systems, which are almost linear on the time scale of the update intervals [6]. Therefore, we have decided to apply a more advanced estimation algorithm to our system than EKF in order to allow our indoor mobile localization system to be superior in the performance of Cricket. Furthermore, besides these indoor positioning systems before mentioned, there is another indoor positioning system, named 'StarLITE', which offers a new concept for ubiquitous robotic space (URS). StarLITE, which is composed of two infrared beacon modules attached on the ceiling of a space and an image sensor equipped on top of a mobile robot, has the robustness of location data and its accuracy as well as the ability to operate not depending on illumination condition, which is not the case for most vision-based approaches [7].

As the first step of our research, we carried out a study to determine which estimation algorithm would be the most fitting for our indoor mobile localization system. Above all, we decided that examining the efficiency as well as appropriateness of the estimation algorithm for our system would be the most important step of our research. For this reason, we investigated advanced estimation algorithms, and then accomplished simulation testing for verifying which algorithm has better performance and suitability; in this research step, we compared Unscented Kalman Filter (UKF) with Unscented Particle Filter (UPF). As a result of the simulation, UKF was determined to be most suitable for our system even though UPF is generally considered as the even better algorithm; because UPF is a compound algorithm of the particle filter and UKF proposal generation [5]. The second step of our research was to perform a practical implementation of UKF into our system; consequently, we could certificate that localization through UKF was remarkably improved over the accuracy of Cricket. The Unscented Kalman Filter can be considered as a compensation algorithm for overcoming effects due to noise factors; that is, these noise factors are memorized and used to estimate the most reliable position. However, in cases that effect from noise exceeds the maximum boundary of noise that is initially defined, the outcome of the estimation

algorithm has a huge possibility of divergence of localization; as a result of such a divergence, it would take too much time to carry out stable localization. This divergence phenomenon is truly attributed to the fact that there would be unexpected external noise, multi-path problems of ultrasound, and unknown effects due to the physical characteristics of ultrasound while measurement/sensing task for localization is performed. To cope with such an unstableness of localization, we presented the beforehand filter algorithm named Pre-filtering, which helps UKF to be more guaranteed and robust on rough impulse noise.

This paper is composed of 5 Sections. Section 1 introduces the overall content of this paper. Section 2 compares the Unscented Kalman Filter with the Unscented Particle Filter, and validates which algorithm is efficient and proper. Section 3 practically implements the Unscented Kalman Filter into our indoor mobile localization system, and certifies its performance through localization results. Section 4 introduces the basic concept of Pre-filtering and its practical application. Section 5 provides a conclusion to this paper.

2. COMPARISON BETWEEN UNSCENTED KALMAN FILTER (UKF) AND UNSCENTED PARTICLE FILTER (UPF)

2.1. Introduction of indoor GPS and its configuration

We developed an indoor mobile localization system, named 'Indoor GPS' [8]. Fig. 1 is a main control module with an ultrasonic receiver (left) and an ultrasonic transmitter (right), respectively. Every module has a DSP chip for realizing outstanding performance. Our system uses two kinds of ultrasonic frequencies, 40kHz & 25kHz, so that 'Indoor GPS' can achieve faster measurement time of ultrasonic sources from beacons than when just one frequency is used for the localization. In the latter case, the ultrasonic sources of 4 beacons need to be transmitted successively in order to avoid interference between their ultrasounds. As a result, more elapsed time for processing in this case is required without doubt. On

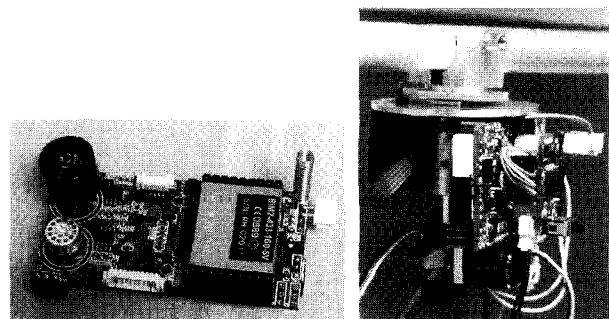


Fig. 1. Indoor GPS developed in KIST.

the other hand, we can save time for acquiring distance data through transmitting two different ultrasonic frequencies simultaneously.

The Indoor GPS adopts a method of ‘Tone Detection’ when distinguishing two different frequencies. Tone Detection allows the Indoor GPS to be less dependent on the angle of US transmission so that the Indoor GPS can make it possible for the localization area to be wider. We analyzed ultrasonic sensor noise pattern of 40kHz and 25kHz in order to certify improvement of independency on the angle of ultrasonic transmission. We measured the time-of-flight lateration according to the change of distance, 0 ~ 5m, and rotational angle, 0 ~ 90°, as in Fig. 2. We calculated RMSE values of each ultrasonic frequency based on absolute position data like Tables 1 and 2. From the result of noise pattern analysis, we could

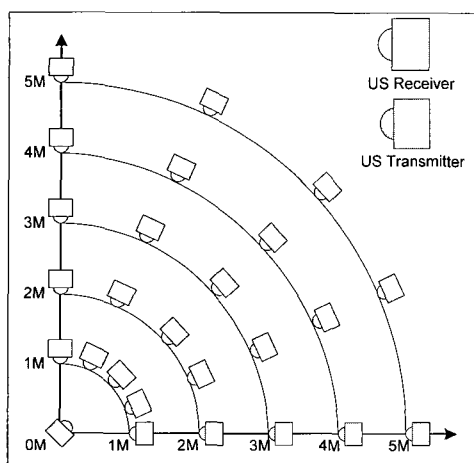


Fig. 2. Measurement setup for analyzing sensor noise pattern.

Table 1. Distance measurement RMSE [mm] of 40 kHz.

	1m	2m	3m	4m	5m
0°	29.00	41.00	21.00	25.00	15.00
20°	18.00	28.00	26.00	22.00	23.00
40°	20.00	28.00	23.00	25.00	24.00
60°	16.00	17.00	30.00	22.00	22.00
90°	34.00	28.00	34.00	X	X

Table 2. Distance measurement RMSE [mm] of 25 kHz

	1m	2m	3m	4m	5m
0°	38.00	39.00	34.00	47.00	38.00
20°	49.00	36.00	28.00	60.00	51.00
40°	46.00	49.00	39.00	45.00	40.00
60°	45.00	53.00	41.00	43.00	36.00
90°	39.00	34.00	34.00	58.00	19.00

certify that maximum sensor noises of 40kHz and 25kHz are within 41.0mm and 60.0mm respectively; furthermore, the average sensor noises of 40kHz and 25kHz are 30mm and 42mm separately. Consequently, it is proven that sensor noise pattern is very regular regardless of alteration of angle and distance.

2.2. Strategy for applying estimation algorithm

The previous model of Indoor GPS has a localization performance that is within ± 80 mm of RMSE for static objects; because, it did use not any estimation algorithm but the Newton-method to get the 3-D position data from time-of-flight lateration. In contrast, the current version of Indoor GPS makes use of an estimation algorithm for enhancing localization performance. The name of the estimation algorithm applied to Indoor GPS is the Unscented Kalman Filter. As broadly known, the EKF is a minimum mean-square-error (MMSE) estimator based on the *Taylor series expansion* of nonlinear functions like process and observation models; in addition, it has been most generally used for indoor localization or navigation systems. However, it often introduces large errors in the estimated statistics of the posterior distributions of the states because the EKF only uses the first order terms of the Taylor series expansion of the nonlinear functions. This defect is evident when the effects of the higher order terms of the *Taylor series expansion* become significant and sometimes lead to divergence of the filter. These defects of the EKF can be complemented by approximating the distribution of the state random variable instead of approximating the non-linear process and observation models. The approximation using distribution of the state random variable is a basic strategy of the Unscented Kalman Filter. The UKF is an advanced application of the scaled unscented transformation; that is, it is a recursive minimum mean-square-error (RMMSE) estimation to propagate the sigma points through the state equation to obtain some high order information, in addition to the first order approximation. The UKF leads to more accurate results than the EKF, and in particular it generates much better estimates of the covariance of the states. Unlike the EKF, it uses the true nonlinear models and rather approximates the distribution of the state random variable. Although UKF is considered as a better estimation algorithm than EKF, the computational time of the Unscented Kalman filter is much greater than the computational time of the extended Kalman filter [9]; furthermore, it is practically true that the Unscented Kalman Filter has a slightly better performance than the Extended Kalman Filter. Nevertheless, even though there has already been a previous application model of UKF for robot position determination which integrates the robot's position and orientation based on an inertial sensor

and odometry using UKF [10], we tried to apply UKF as an estimation algorithm to our indoor mobile localization system only using ultrasonic sensing as another application model for the purpose of reconfirming that UKF could also contribute to improve the localization performance of the indoor localization system.

2.3. Simulation of UKF and UPF and its results

Before adopting UKF as an estimation algorithm applied to our system, we made an effort to utilize the Unscented Particle Filter for the performance enhancement of our localization system, Indoor GPS. The Unscented Particle Filter (UPF) is a new filter that results from using a UKF for proposal distribution generation within a particle filter framework. That is, the Unscented Particle Filter takes advantage of UKF as well as of Particle Filter; resultantly, UPF is generally regarded as an advanced estimation algorithm superior to UKF. However, we could not ensure that UPF would demonstrate relatively better performance than UKF since the performance of UPF is totally dependent on the accuracy of the sensor. For this reason, we have decided to carry out a simulation test in order to determine a more suitable estimation algorithm for our system. First of all, we chose ellipsoidal motion as

our simulation scenario because ellipsoidal motion is so complicated and severe that we can exactly test the performance of a simulated estimation algorithm; that is, the more complicated the motion is, the better the performance test is. The trajectory of ellipsoidal motion is composed of 6 sections; sections 1 and 4 are translational motion with changing acceleration, on the other hand, sections 2, 3, 5, and 6 are circular motion with changing angular acceleration as shown in Fig. 3 and Table 3.

Fig. 4 is the simulation result of ellipsoidal motion for demonstrating the difference of localization performance of UKF and UPF; the estimation locus of UKF is red-lined pattern, and the one of UPF is blue-lined pattern. As shown in Fig. 5, there is not a huge difference of localization performance between UKF and UPF; however, the localization through UKF is slightly better than the one through UPF even though UPF is generally a more advanced algorithm than UKF. As a result of the simulation, we could certify

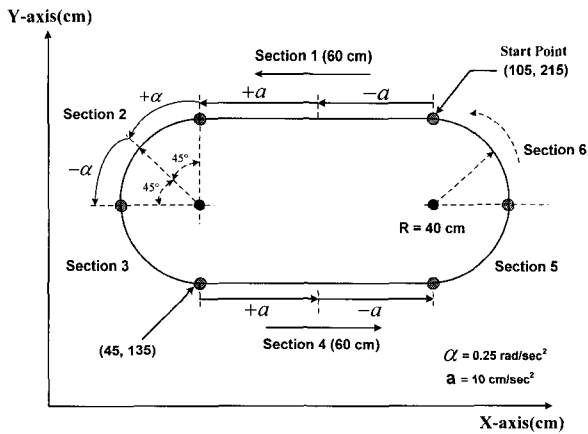


Fig. 3. Virtual motion trajectory for simulation.

Table 3. The condition of simulation.

Total Localization Step	300steps	
Sample Time	100mm sec.	
Translational Acceleration	10cm/sec ²	
Angular Velocity	0.25rad/sec ²	
Start point (x, y)	(1050, 2150)mm	
Process Noise	X	10mm
	Y	10mm
	Z	1mm
Measurement Noise	±30mm for all beacons	

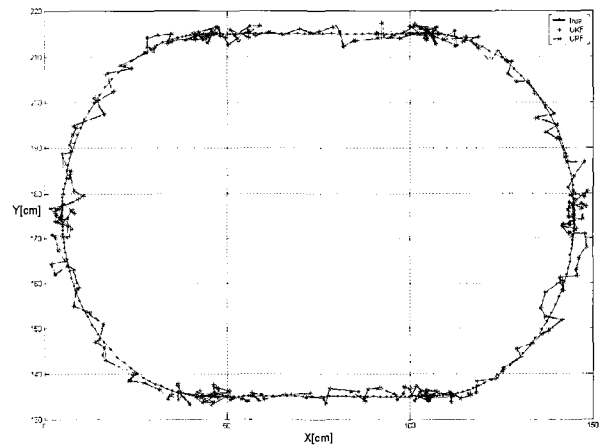
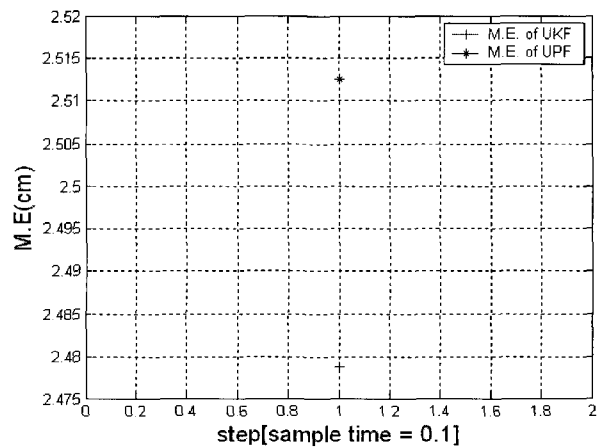


Fig. 4. Simulation result of ellipsoidal motion.



	Mean Error (cm)
UKF	2.4787
UPF	2.5125

Fig. 5. Mean error of UKF and UPF.

that UPF is not always superior to UKF in case that sensor value, which is used for re-sampling in UPF framework, is not perfectly guaranteed; that is, there exists noise elements in sensor value. Furthermore, UKF can be thought of as a more suitable algorithm for localization than UPF since UPF requires higher computational cost than UKF. Consequently, we have decided to apply the more practical UKF to our indoor mobile localization system.

3. UKF IMPLEMENTATION AND LOCALIZATION RESULT

3.1. The unscented Kalman filter (UKF) and its implementation

The Unscented Kalman Filter (UKF) as shown in Algorithm 1 is a straightforward application of the scaled unscented transformation to recursive minimum mean-square-error (RMMSE) estimation (Julier and Uhlmann 1997). We applied the Unscented Kalman Filter to Indoor GPS in order to not only enhance the localization performance of Indoor GPS but also make the localization algorithm applied to the general indoor localization system to be more sophisticated. We designed our systems on the basis of the Position-Velocity (PV) modeling as well as the Position-Velocity-Acceleration (PVA) modeling since position, velocity, and acceleration are the interested elements; moreover, it is easy to define these parameters as state variables of our system's dynamic equation. Therefore, we set the state variables of the dynamic equation as a mobile object's position, velocity, and acceleration.

Algorithm 1: The Unscented Kalman Filter (UKF)

Define States:

- \bar{x}_k : States
- y_k : Measurements
- λ : Scaling parameter
- K_k : Kalman gain
- Q : State noise covariance
- R : Measurement noise covariance

1. Initialize with:

$$\begin{aligned} \bar{x}_0 &= E[x_0] \\ P_0 &= E[(x_0 - \bar{x}_0)(x_0 - \bar{x}_0)^T] \\ \bar{x}_0^a &= E[x^a] = [\bar{x}_0^T \ 0 \ 0]^T \\ P_0^a &= E[(x_0^a - \bar{x}_0^a)(x_0^a - \bar{x}_0^a)^T] = \begin{bmatrix} P_0 & 0 & 0 \\ 0 & Q & 0 \\ 0 & 0 & R \end{bmatrix} \end{aligned}$$

2. Procedure:

For time k do

Generate sigma points:

$$\chi_{k-1}^a = [\bar{x}_{k-1}^a \ \bar{x}_{k-1}^a \pm \sqrt{(n_a + \lambda)P_{k-1}^a}]$$

Time update:

$$\chi_{k/k-1}^x = f(\chi_{k-1}^x, \chi_{k-1}^v)$$

$$\bar{x}_{k/k-1} = \sum_{i=0}^{2n_a} W_i^{(m)} \chi_{i,k/k-1}^x$$

$$P_{k/k-1} = \sum_{i=0}^{2n_a} W_i^{(c)} [\chi_{i,k/k-1}^x - \bar{x}_{k/k-1}] [\chi_{i,k/k-1}^x - \bar{x}_{k/k-1}]^T$$

$$y_{k/k-1} = h(\chi_{k-1}^x, \chi_{k-1}^n)$$

$$\bar{y}_{k/k-1} = \sum_{i=0}^{2n_a} W_i^{(m)} y_{i,k/k-1}^x$$

Measurement update equations:

$$P_{\bar{y}_k \bar{y}_k} = \sum_{i=0}^{2n_a} W_i^{(c)} [y_{i,k/k-1} - \bar{y}_{k/k-1}] [y_{i,k/k-1} - \bar{y}_{k/k-1}]^T$$

$$P_{x_k y_k} = \sum_{i=0}^{2n_a} W_i^{(c)} [\chi_{i,k/k-1}^x - \bar{x}_{k/k-1}] [y_{i,k/k-1} - \bar{y}_{k/k-1}]^T$$

$$K_k = P_{x_k y_k} P_{\bar{y}_k \bar{y}_k}^{-1}$$

$$\bar{x}_k = \bar{x}_{k/k-1} + K_k (y_k - \bar{y}_{k/k-1})$$

$$P_k = P_{k/k-1} - K_k P_{\bar{y}_k \bar{y}_k} K_k^T$$

End for

3.2. Performance comparison with the previous indoor

GPS through localization test for static position

Above all, in order to certify the improvement of localization performance of Indoor GPS through comparing the current version of Indoor GPS using UKF with the previous version of Indoor GPS using Newton-method, we performed localization task for static object on which the main control module with ultrasound receiver is mounted. In the experimental environment as shown in Fig. 6, we carried out a real

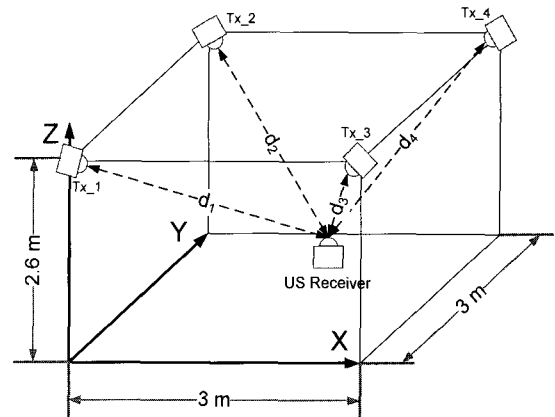


Fig. 6. Experimental dimension and configuration.

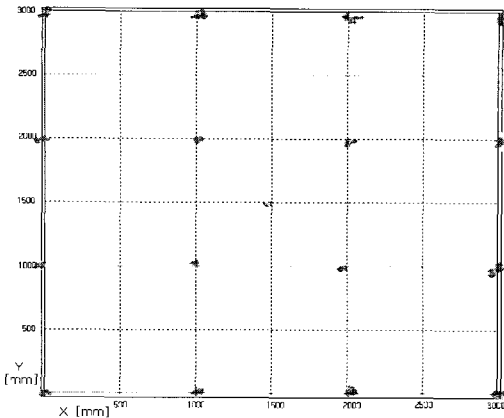


Fig. 7. Localization result for static position.

Table 4. RMSE of localization result for static position.

Number	Absolute Position Value			RMSE of coordinate [mm]
	X	Y	Z	
1	0000	0000	0610	13.281377
2	0000	1000	0610	12.628899
3	0000	2000	0610	14.236698
4	0000	3000	0610	14.074974
5	1000	0000	0610	13.853569
6	1000	1000	0610	12.169404
7	1000	2000	0610	13.533700
8	1000	3000	0610	20.891701
9	2000	0000	0610	14.797277
10	2000	1000	0610	12.561878
11	2000	2000	0610	12.104473
12	2000	3000	0610	20.125955
13	3000	0000	0610	29.406081
14	3000	1000	0610	14.585087
15	3000	2000	0610	17.092725
17	1500	1500	0610	16.790702

localization test on 17 static positions.

As indicated in Fig. 7 and Table 4, it is proven that UKF plays an important role in improving the localization accuracy of Indoor GPS; accordingly, the accuracy of localization is within about ± 20 mm except for the 13th position's localization. In the case of the 13th position, there seemed to be some definite interference causes, such as multi-path effect, harsh external sound noise, etc. In addition, there might be poorer state of US transmission and reception between modules due to manual arrangement of every US beacons' transmitter angle. When compared with the localization performance of previous Indoor GPS,

which has about ± 80 mm of localization accuracy, the current Indoor GPS are shown to be a much more accurate localization system.

3.3. Localization test for dynamic object and performance analysis

The next experiment for evaluating the performance of Indoor GPS is to perform localization for the dynamic target of circular motion. We set up experimental configuration as indicated in Fig. 8. The main control module of Indoor GPS is mounted on the rod of a circular motion system, and can be moved and fixed freely so that the radius of circular motion can vary; minutely speaking, the radius of circular motion is the distance from the center of circular motion to the ultrasonic receiver of the main control module. We accomplished the localization test with altering radius (500mm~1500mm) and angular velocity (0.1~0.4 rad/sec) of the circular motion system.

As shown in Table 5 and Fig. 9, we get RMSE (Root-Mean-Square-Error) corresponding to 200 steps against the absolute coordinate data based on a trajectory of our circular motion system; we could certify the accuracy of localization because circular motion is within about 50mm under the condition that the radius is shorter than 1000mm, and angular velocity is slower than 0.2 rad/sec.

In addition, as given in Fig. 10, it is certified that the accuracy of localization comes to be degraded

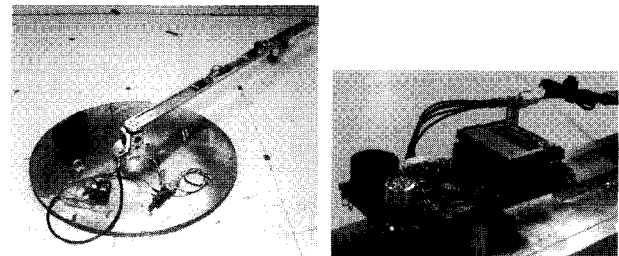
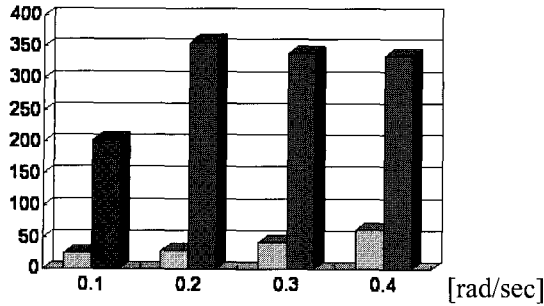


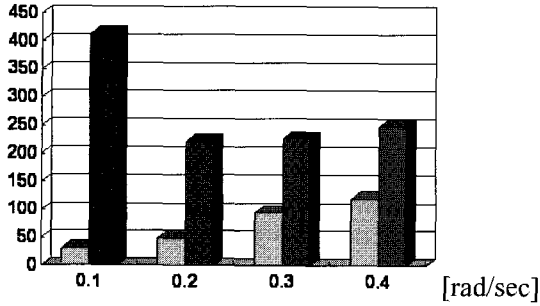
Fig. 8. Experimental setup for dynamic target.

Table 5. RMSE [mm] of localization through UKF and Newton-Method for dynamic target.

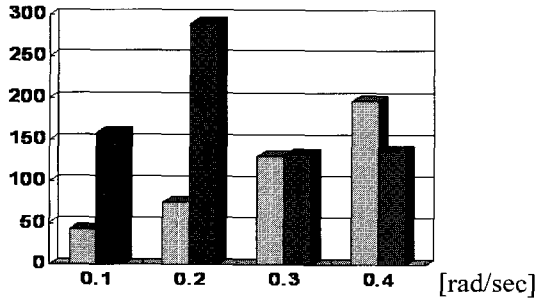
radius \ ω	0.1 (rad/sec.)		0.2 (rad/sec.)	
	UKF	N.M.	UKF	N.M.
500mm	25.54	203.23	29.12	357.1
1000mm	31.57	412.71	50.25	222.4
1500mm	42.52	158.56	75.63	290.2
radius \ ω	0.3 (rad/sec.)		0.4 (rad/sec.)	
	UKF	N.M.	UKF	N.M.
500mm	41.181	339.3	62.86	335.4
1000mm	95.53	226.71	120.2	249.5
1500mm	130.85	132.72	197.0	136.2



(a) Radius = 500mm.



(b) Radius = 1000mm.



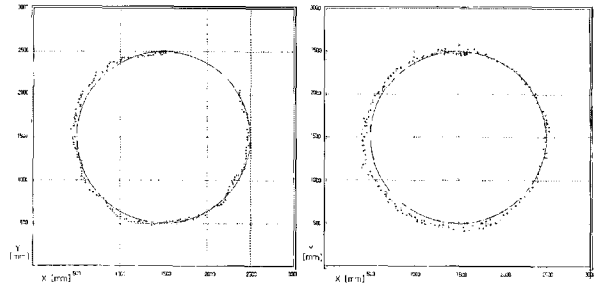
(c) Radius = 1500mm.



Fig. 9. RMSE [mm] of UKF and Newton-Method for dynamic target.

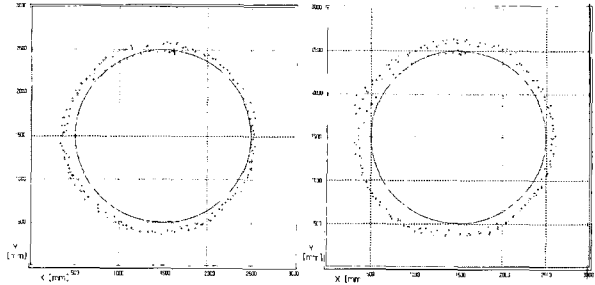
when angular velocity increases. The gravest reason of accuracy degradation related to the increase of angular velocity is the fact that sampling time for localization is too slow to estimate the position of moving target with high angular velocity. The average sampling time of Indoor GPS is about 250mm sec while localization task is performed. The reason why the elapsed time for progressing one localization step is about 250mm sec is that wireless communication is used for communication between a personal computer and the main control module mounted on the rod of the circular motion system.

On the one hand, the sampling time of 250mm second is enough to perform localization task at slow angular velocity. On the other hand, it is occasionally hard for this sampling time to precisely localize a moving target with high angular velocity since the estimation algorithm needs basically even more



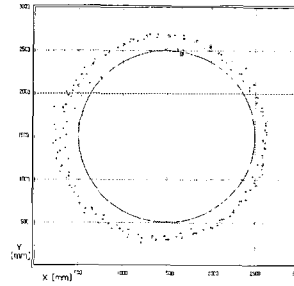
(a) $\omega = 0.1$ rad/sec.

(b) $\omega = 0.2$ rad/sec.



(c) $\omega = 0.3$ rad/sec.

(d) $\omega = 0.4$ rad/sec.



(e) $\omega = 0.5$ rad/sec.

Fig. 10. Localization result for dynamic target of circular motion ($\omega = 0.1 \sim 0.5$ rad/sec).

prediction and update steps in order to attain estimation as exact as possible whenever the motion speed increases. We concluded that the accuracy in the harsh motion condition such as fast angular velocity (0.4rad/sec) and maximum radius of motion (1500mm) may become better if the wireless communication is replaced with wired communication; that is, much more prediction and update steps of estimation algorithm could be accomplished in the case that the sampling time comes to be shortened.

3.4. Some issues regarding the kidnapped state

We've tested the performance of our proposed indoor positioning system under the condition of the kidnapped state through compulsory covering one beacon which was transmitting ultrasonic burst. As a result, the positioning result of receiver had been diverged. In addition, it took large amount of time for receiver to get correct position data through the process of convergence. It is a very natural phenomenon that divergence appears when any kidnapped state occurs because UFK needs at least

four distance data from beacons to receiver. Therefore, we can control programmatically the scheme of localization in order to overcome this negative effect. That is, when it comes to the condition that such a kidnapped state occurred, we can realize localization of receiver only using three distance data through Newton-method instead of UKF until four distance data successfully appear; however, we still have a limited condition that only one distance data is kidnapped among a total of four distance data. Of course, the accuracy of localization using three distance data through the Newton-method is not reliable. However, it is effective to prevent localization from going to divergence even though it is insufficient.

4. STABILIZATION THROUGH PRE-FILTERING

4.1. Instability phenomenon of localization

There were occasionally receptions of unstable ultrasonic sources when we obtained the 3 dimensional position data either of a moving target or of static object. This comes from the possibility that an ultrasonic receiver does not get a pure ultrasonic source from an ultrasonic transmitter but rather an unstable or polluted ultrasonic source affected by multi-paths or unexpected external inaudible sound. Consistently, we could experience that an impulsive error happened while localization of a moving object was carried out. Such an impulsive error causes the locus of localization not only to be separated from the expected position, but also sometimes to be divergent; accordingly, the performance of localization comes to be degraded.

4.2. The Pre-filtering

Therefore, we constructed an additional filter algorithm named 'Pre-filtering' as shown in Algorithm 2 in order to overcome the instability phenomenon of localization through removal of such unstable and unreliable ultrasonic sources.

Algorithm 2: The Pre-filtering

Define States:

$$X_k : \text{Position States} = [x_k \ y_k \ z_k]^T$$

$$V_k : \text{Velocity States} = [V_{x/k} \ V_{y/k} \ V_{z/k}]^T$$

$$A_k : \text{Acceleration States} = [A_{x/k} \ A_{y/k} \ A_{z/k}]^T$$

$$T_S : \text{Sampling Time}$$

$$X_k^P : \text{Position States for pre-filtering at k step} \\ = [x_k^P \ y_k^P \ z_k^P]^T$$

$$D_{next} : \text{Next Measurements}$$

$$= [d_{next/0} \ d_{next/1} \ d_{next/2} \ d_{next/3}]^T$$

where $d_{next/i}$ is a real distance data from i^{th}

beacon to receiver.

σ_i : the root-mean-square-error of measurement with a connection of i^{th} beacon.

1. Get the position states of k^{th} step for pre-filtering using the updated states by UKF at k^{th} step:

$$X_k^P = X_k + V_k * ST + \frac{1}{2} * A_k * T_S * T_S \text{ in PVA mode}$$

$$X_k^P = X_k + V_k * T_S \text{ in PV mode}$$

2. Find distance values from receivers to 4 beacons using the position states through step 1:

$$D0 = \sqrt{(x_k^P - 0)^2 + (y_k^P - 0)^2 + (z_k^P - Z_0)^2}$$

$$D1 = \sqrt{(x_k^P - 0)^2 + (y_k^P - Y_1)^2 + (z_k^P - Z_1)^2}$$

$$D2 = \sqrt{(x_k^P - X_2)^2 + (y_k^P - 0)^2 + (z_k^P - Z_2)^2}$$

$$D3 = \sqrt{(x_k^P - X_3)^2 + (y_k^P - Y_3)^2 + (z_k^P - Z_3)^2}$$

i.e., D0 is a distance from receiver to 0^{th} beacon.

Where the 4 beacons' positions are the following.

$$\text{Beacon 0} = (0, 0, Z_0)$$

$$\text{Beacon 1} = (0, Y_1, Z_1)$$

$$\text{Beacon 2} = (X_2, 0, Z_2)$$

$$\text{Beacon 3} = (X_3, Y_3, Z_3)$$

in rectangular coordinate (x, y, z)

3. Validate the next measurement data:

$$\text{if } D0 - 5 * \sigma_0 \leq d_{next/0} \leq D0 + 5 * \sigma_0$$

then $d_{next/0}$ is valid.

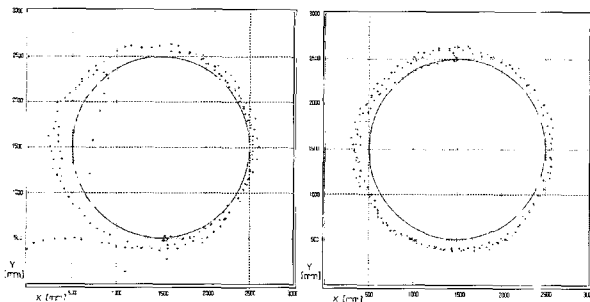
4. If all measurements are valid, execute UKF localization of $k+1^{\text{th}}$ step using the next measurements. If not, the next measurements are filtered. Then, postpone UKF localization of $k+1^{\text{th}}$ step until next measurements are valid.

The basic procedure of 'Pre-filtering' is as follows. First, calculate the next position coordinate using the estimated result of pre-step through UKF. Second, get four distance data from 4 beacons to receiver using a position coordinate acquired from the first step. These distance data are criteria for validating next measurements; that is, the result of step 2 is a mean value of normally distributed population of measurements. Third, determine the validity of the next measurements. The Pre-filtering does not perform its function for continuous harsh noise since divergence problem occurs when sensor values are continually examined by Pre-filtering. When the harsh external noise occurs continually, it is thought of as the situation of localization failure because such an environment affected by continuous harsh noise makes it impossible for Indoor GPS to carry out localization successfully.

4.3. Experiment for validating the effect of Pre-filtering and its results

For substantiating the performance of Pre-filtering when unreliable ultrasonic source happens, we forced the measurement value due to 0th beacon's ultrasonic source to be zero at the 50th, 100th, and 150th step when the condition of circular motion is that angular velocity is 0.3 rad/sec and radius is 1000mm; in this condition, the RMSE of localization is 95.53mm from Table 5. As shown in (a) of Fig. 11, we can confirm that the performance of UKF localization is deteriorated when the Pre-filtering does not operate.

On the other side, operation of Pre-filtering makes the UKF localization more stable and reliable as shown in (b) of Fig. 11. For a more practical test, we made an external ultrasound noise generator as indicated in Fig. 12. The external ultrasound noise generator plays a role in interfering real ultrasound sources from 4 ultrasound transmitters. The external ultrasonic noise generator was triggered to fire ultrasound 10times for localization without Pre-filtering and 2 times for localization with Pre-filtering during 1 cycle of circular motion of which the condition is that angular velocity is 0.2rad/sec and radius is 1000mm; in this condition, the RMSE of localization is 50.25mm from Table 5. As portrayed in Fig. 13, we can also certify that Pre-filtering helps the Unscented Kalman Filter overcome bad effects due to abrupt external noise; accordingly, Pre-filtering contributes to the stabilization of localization through UKF.



(a) without Pre-filtering. (b) with Pre-filtering.

Fig. 11. Pre-filtering test - (1).

($\omega = 0.3\text{rad/sec}$, radius = 1000mm)

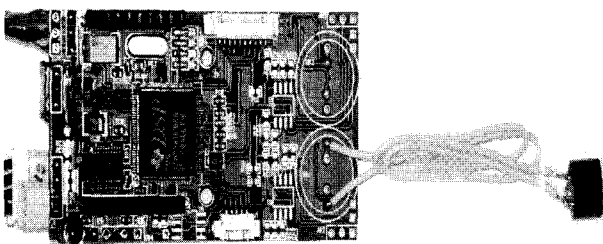
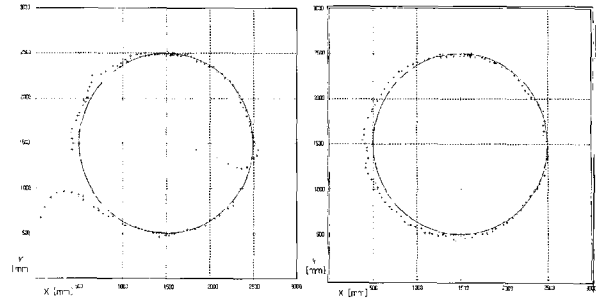


Fig. 12. External ultrasound noise generator.



(a) without Pre-filtering. (b) with Pre-filtering.

Fig. 13. Pre-filtering test - (2).

($\omega = 0.2\text{rad/sec}$, radius = 1000mm)

5. CONCLUSION

Several kinds of indoor localization systems have been developed and researched for many years. However, they have failed to realize precise localization performance sufficient to satisfy the requirement of localization accuracy for ubiquitous computing. Therefore, we have developed an accurate and reliable indoor mobile localization system using Unscented Kalman Filter (UKF). Furthermore, we certified that the Unscented Particle Filter (UPF) is not always a better estimation algorithm than the Unscented Kalman Filter (UKF) through simulation test. It is proven that UPF is not proper for a system using sensor value including noise factors. Consequently, since there are noise factors in sensor value, we adopted UKF as an estimation algorithm for localization so that we could accomplish the improvement of localization performance. Also, it is certified that Indoor GPS of KIST is superior to any other indoor localization system using ultrasound.

We found out that instability phenomenon happens when any external harsh noise occurs. In this case, localization through UKF comes to be unstable and as a result the performance is degraded; moreover, the failure of localization occasionally occurs. Therefore, we have presented an effective filter algorithm named Pre-filtering, which helps the UKF overcome severe disturbance for sensor measurement. Nevertheless, Pre-filtering cannot overcome continuous external noise in order to avoid divergence problem. Therefore, the development of a new algorithm for overcoming such a continuous external noise must be carried out as a future work in order to realize eventually ubiquitous computing.

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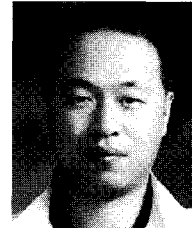
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