State Estimation Approach for Depth Sensor’s Posture Attached to a Vehicle or a Human Body*

Masahiro Tanaka†

The author has been developing a navigation system for safety for mobile robots, mobility scooters and pedestrians by using depth sensors which can capture range data of image size. If the geometrical relation between the sensor and the space is completely known, each point of the captured range data can be classified into three groups: upper than the ground, on the ground, and lower than the ground. However, it is essential to be able to deal with the unpredictable change of the posture of the sensor due to the movement of the attached body. The author already developed a real-time estimation scheme of the posture including pitch angle, roll angle, and height from the observed data in the framework of optimization. In this paper, the author proposes an estimation scheme based on the state space model and apply Extended Kalman filter for the same application problem. We will compare the algorithms by experimental results and will show the usefulness of the proposed algorithm.

1. Introduction

This paper considers the problem of estimating unknown parameters of the posture of a depth sensor attached to an unstable dynamic object such as AGV (Automated Guided Vehicle), a mobility scooter, a bicycle or a person, where the pitch and roll angles and the height of the sensor from the ground may change as it moves.

Figure 1 and 2 show examples of the sensor attached to a dynamic object such as a mobility scooter or a human body.

Assuming that the attachment of the sensor is with known pitch and roll angles at a known height, it is easy to express the relation between the polar coordinate from the sensor and the Cartesian coordinate of the environment. Thus we can figure out the Cartesian coordinate from the polar coordinate data. However, we have to cope with the fact that the posture always changes.

The author first considered the case when only the pitch angle was subject to vary. This happens when a depth sensor is attached to a mobility scooter and it goes straight on a rough passage. The author also considered the case when the vehicle turns[1]. When the sensor is attached to the basket of the mo-

---

* Manuscript Received Date: May 20, 2013
† Faculty of Intelligence and Informatics, Konan University; 8-9-1 Okamoto, Higashinada ward, Kobe city, Hyogo 658-8501, JAPAN

Key Words: depth sensor, ground detection, optimization, extended Kalman filter, robust estimation, obstacle detection.
bility scooter, the roll angle changes as the driver tilts the handlebar. The height of the sensor position also changes in this case.

As a common feature of the observed data from a mobile body, the sensor’s state such as the posture and/or the position always changes. If there is no external sensor to capture the sensor’s state, what we can do is to estimate the sensor’s state from the observed data from it. The problem is called “localization” in robotics community, where the environmental information is given a priori. The author and his colleagues considered the localization problem when there are obstacles in the environment[2]. In the paper, the obstacles do not appear in the environmental information, and the mixture model for the observation data was assumed, where one of the probability density function (PDF) expressed the obstacle model.

Our current problem discussed in this paper is different from our previous paper[2] in the sense that there is no environmental model. Instead, we assume that most part of the acquired data shows the ground surface. Obstacles are considered to emit another data source.

Hence, if the range data in the view is almost from the ground surface, the depth sensor captures a set of range data at a certain instant looking at the road or floor surface, the estimated height of each observed data point should be almost zero.

We formulated this problem as an optimization problem where the objective function was the sum of the square of estimated vertical positions, and the decision values were the pitch and roll angles and the height of the sensor position[1]. In this formulation, it is necessary to eliminate data instances which seem to be not from the ground surface. Hence we formulated the problem as the robust estimation problem in[3]. This problem can be validated only when most of the data is from the ground. To deal with the case when there are substantial amount of objects in the view, some robust optimization algorithm was needed[3]. The sensor noise and the roughness of the ground could not be separately treated.

In this paper, an estimation scheme based on extended Kalman filter (EKF) is proposed, where the problem is formulated by a nonlinear state space model, and the error is treated as random values. The state vector to be estimated is a 3-dimensional vector consisting of the pitch and roll angles and the height. The experimental results will show the usefulness of the proposed algorithm.

2. Observation Model

2.1 Case when Sensor is Fixed Parallel to Ground

Here we define the observation model when the sensor is fixed straight looking horizontally parallel to the ground. The observation model depends on the sensor. We consider the case of using Kinect for Windows1 or Xtion Pro Live2.

Figure 3 shows the relation between the polar coordinates and the Cartesian coordinate when the sensor is fixed horizontally.

![Fig. 3](image)

The available data for one shot is a set \{rij; i = 1, ..., nV, j = 1, ..., nH\}, where i corresponds to the vertical position from top to bottom, and j corresponds to the horizontal position from left to right. The relation between the number i and its corresponding depression angle \(\theta_i\) (see Fig.3) is assumed to be

\[
\theta_i = \frac{\angle V}{n_V - 1} (i - \frac{n_V - 1}{2}), \quad i = 1, ..., n_V
\]  

(1)

Also, index j corresponds to the horizontal position from left to right. The relation between the number j and its corresponding yaw angle \(\phi_j\) is also assumed to be

\[
\phi_j = \frac{\angle H}{n_H - 1} (j - \frac{n_H - 1}{2}), \quad j = 1, ..., n_H
\]  

(2)

where \(\angle H\) and \(\angle V\) are horizontal and vertical view angles found in the specification of the sensor, respectively. Assuming that each observation \(r_{ij}\) shows the range from the sensor position to the reflected point at \((\theta_i, \phi_j)\), the relation between the Cartesian coordinate and the polar coordinate is

\[
\begin{bmatrix}
x_{ij} \\
y_{ij} \\
z_{ij}
\end{bmatrix} = \begin{bmatrix}
r_{ij}\cos \theta_i \cos \phi_j \\
r_{ij}\cos \theta_i \sin \phi_j \\
-r_{ij}\sin \theta_i
\end{bmatrix} + \begin{bmatrix}
0 \\
0 \\
h
\end{bmatrix}
\]  

(3)

2.2 Case when Sensor has Arbitrary Posture

It is very natural to assume that the sensor cannot be fixed to the original posture but has arbitrary posture when it is attached to any mobile objects. Hence we consider the case when the center beam of the sensor has the depression angle \(\alpha\) and the roll angle \(\psi\) as shown in Fig.4.

---

1Product of Microsoft Corporation
2Product of ASUSTeK Computer Inc.
Then the relation between the angles $\alpha$, $\psi$, $\theta_i$, $\phi_j$ and the Cartesian coordinate is given by

$$
\begin{bmatrix}
    x_{ij} \\
    y_{ij} \\
    z_{ij}
\end{bmatrix} = R_x(\psi) R_y(\alpha) \begin{bmatrix}
    r_{ij} \cos \theta_i \cos \phi_j \\
    r_{ij} \cos \theta_i \sin \phi_j \\
    -r_{ij} \sin \theta_i
\end{bmatrix} + \begin{bmatrix}
    0 \\
    0 \\
    h
\end{bmatrix}
$$

(4)

where $R_x(\psi)$ is the rotation around $x$-axis, and $R_y(\alpha)$ is the rotation around $y$-axis given by

$$
R_x(\psi) = \begin{bmatrix}
1 & 0 & 0 \\
0 & \cos \psi & \sin \psi \\
0 & -\sin \psi & \cos \psi
\end{bmatrix}
$$

(5)

$$
R_y(\alpha) = \begin{bmatrix}
\cos \alpha & 0 & \sin \alpha \\
0 & 1 & 0 \\
-\sin \alpha & 0 & \cos \alpha
\end{bmatrix}
$$

(6)

To make distinction of the observation point categories between

- **(g)round** : from the ground surface
- **(s)horter** : from an obstacle
- **(l)onger** : from a ditch or a hole

we need models corresponding to the cases.

### 2.3 Data Calibration

The model described above is an assumption, and the geometrical relation between the pixel position and its corresponding 3D position is not indicated officially for Kinect or Xtion. Actually, by conducting experiments using Xtion, we noticed that the measured data does not follow the model described above. When a set of data was captured from 1m away from the wall by setting the sensor center beam perpendicular to the wall, all the range data was almost the same. However, the distance from the camera to the wall points are not uniform theoretically; the range in the center are small and the range gradually become large as the point goes away from the center. This means that the measured data are not the range data themselves, but are modified in the sensor itself, probably meant for applications. By using data, we have to modify the data so that it can be used by the model described above by

$$
r_{ij} := \frac{r_{ij}}{\cos \theta_i \cos \phi_j}
$$

(7)

We don’t change the original model so that it can be used for other sensors for which the model strictly follows (e.g. URG sensors of Hokuyo Co. in one dimension).

### 3. Our Previous Approach for Parameter Estimation

We already developed an estimation scheme of the posture of the sensor by the optimization-based approach[1],[3]. In this section, we will briefly explain this approach.

From the observation equation (4), we have

$$
z_{ij} = h - r_{ij}(\sin \alpha \cos \psi \cos \theta_i \cos \phi_j + \cos \alpha \cos \psi \sin \theta_i + \sin \psi \cos \theta_i \sin \phi_j)
$$

(8)

and, if the observation point $(i,j)$ captures a point on the ground, we have

$$
z_{ij} \approx 0
$$

Thus, we can pose a local minimization problem:

$$
\min_{\alpha, \psi, h, (i,j) \in G} \sum_{(i,j) \in G} (h - r_{ij}(\sin \alpha \cos \psi \cos \theta_i \cos \phi_j + \cos \alpha \cos \psi \sin \theta_i + \sin \psi \cos \theta_i \sin \phi_j))^2
$$

(9)

where $G$ is the set of points on the ground. However, $G$ is unknown at this moment. The algorithm we proposed was as follows.

1. Set unknown values of parameters $\alpha, \psi, h$ at certain reasonable values.
2. Based on the assumed parameter values, we compute equation (8) and form the set $G$ by the tuple $(i,j)$ whose $z_{ij}(k)$ was approximately zero.
3. Based on the assumed $G$, the minimization problem (9) is performed.
4. Go back to Step (2).

Since the minimization problem incurs a heavy computational load, we took an approach to pick up only a small portion of the points, e.g. using 1 out of 8 × 8 points. Furthermore, the minimization was carried out by using one step Newton method which usually needs substantial amount of iterations.

We got a successful result by this approach. However, there were some drawbacks. One point was that all the deviation from $z = 0$ was evaluated by using one model (8), and hence it was difficult to make distinction between the sensor error and the obstacle in the model. A drawback example due to this point will be shown in the comparison study in section 6.3.

### 4. New Approach Based on State Space Model

#### 4.1 State Vector and Its Dynamic Model

We consider the case when the state vector $q$ consists of the pitch angle $\alpha$, roll angle $\psi$ and the height $h$, i.e.

---

1. We have changed some part of the model, so the gradient and Hessian matrix should be changed accordingly.
\[ q = \begin{bmatrix} q_1 \\ q_2 \\ q_3 \end{bmatrix} = \begin{bmatrix} \alpha \\ \psi \\ h \end{bmatrix} \]

By considering the mechanism of the transition of these parameters, it is reasonable to assume a random walk model

\[ q(k+1) = q(k) + w(k) \]

where

\[
E[w(k)] = 0 \\
E[w(k)w^T(l)] = Q\delta_{kl} = \text{diag}(q_\alpha, q_\psi, q_h)\delta_{kl}
\]

where \(\delta_{kl}\) is the Kronecker's delta. The values of the variances depend on the dynamic properties of the system and the sampling time.

### 4.2 Observation Model

#### 4.2.1 Case of Ground Surface

If the \((i,j)\)-th beam captures the ground, the captured point’s value \(z_{ij}(k)\) is zero. Thus, by setting \(z_{ij}(k) = 0\) on equation (4), we have the nonlinear observation equation

\[ r_{ij}(k) = \frac{h(k)}{\beta(k)} \]  \hspace{1cm} (11)

where

\[
\beta(k) = \sin\alpha\cos\psi\cos\theta_i\cos\phi_j + \cos\alpha\cos\psi\sin\theta_i \\
+ \sin\psi\cos\theta_i\sin\phi_j
\]  \hspace{1cm} (12)

Since this function is nonlinear with respect to the state variables \(\alpha(k), \psi(k), h(k)\), we rewrite this one by using the symbol of nonlinear function as

\[ f_{ij}(q) = \frac{q_3}{\beta(q_1, q_2)} \]  \hspace{1cm} (13)

where

\[
\beta(q_1, q_2) = \sin q_1 \cos q_2 \cos \theta_i \cos \phi_j + \cos q_1 \cos q_2 \sin \theta_i \\
+ \sin q_2 \cos \theta_i \sin \phi_j
\]  \hspace{1cm} (14)

By aligning these observation equations (11) and (13) into a column vector, we have

\[ r(k) = f(q(k)) + e^{(g)}(k) \]  \hspace{1cm} (15)

where

\[ r = [r_{11} \cdots r_{1N} \cdots \cdots r_{M1} \cdots r_{MN}]^T \]

or

\[ r_{ij}(k) = f_{ij}(q(k)) + e^{(g)}_{ij}(k) \]  \hspace{1cm} (16)

where \(M\) is the number of vertical pixels used for parameter estimation and \(N\) is the horizontal one. Note that \(e^{(g)}_{ij}(k)\) is the measurement noise. This includes the actual sensor noise due to the precision limit of its spec, and the error due to the geometrical measurement difference between the model and the actual sensor’s property. The PDF \(p_y(e^{(g)}_{ij}(k))\) is assumed to be a Gaussian with zero mean and variance \(\sigma_y^2\). Thus

\[ p_y(r_{ij}(k)|f_{ij}(k)) = N(r_{ij}(k)|f_{ij}(k), \sigma_y^2) \]  \hspace{1cm} (17)

#### 4.2.2 Case of Obstacle

This is the case when the observation \(r_{ij}(k)\) reflects an obstacle. In this case, the observed range value is shorter than the case of ground surface, since obstacles disturb the signal before it reaches the ground. We call it “short” case. Since the position of obstacles cannot be specified, we define

\[ r_{ij}(k) = e^{(s)}_{ij}(k) \]  \hspace{1cm} (18)

where its probability density function is given by

\[
p_s(e^{(s)}_{ij}) = \begin{cases} \frac{1}{f_{ij}(q)} & \text{if } 0 < e^{(s)}_{ij}(k) \leq f_{ij}(q(k)) \\ 0 & \text{otherwise} \end{cases} \]  \hspace{1cm} (19)

#### 4.2.3 Case of Hole or Ditch

This is the opposite case of the previous one. If there is a hole of a ditch, the signal goes deeper than the ground surface, thus the range is longer than the range to the ground surface. We call it “long” case. We define

\[ r_{ij}(k) = e^{(l)}_{ij}(k) \]  \hspace{1cm} (20)

where its probability density function is given by

\[
p_l(e^{(l)}_{ij}) = \begin{cases} \frac{1}{r^* - f_{ij}(q)} & \text{if } f_{ij}(q(k)) \leq e^{(l)}_{ij}(k) \leq r^* \\ 0 & \text{otherwise} \end{cases} \]  \hspace{1cm} (21)

where \(r^*\) is the measurement limit, and it is approximately 10m.

#### 4.2.4 Overall PDF Model

Based on the PDFs defined previously, we assume the following mixture PDF\([4],[2]\)

\[
p(r_{ij}(k)|q(k)) = P_g \cdot p_y(r_{ij}(k)|f_{ij}(k)) + P_s \cdot p_s(e_{ij}(k)|f_{ij}(k)) + P_l \cdot p_l(e_{ij}(k)|f_{ij}(k)) \]  \hspace{1cm} (22)

where the second term represents the “short” case, and the third term represents the “long” case. The prior probability \(P_s\) should be set appropriately according to the amount of obstacles in the view, and the \(P_l\) should be zero if there is no possibility of holes or ditches.

### 5. State Estimation by EKF

#### 5.1 Derivation of Jacobian

EKF is a semi-optimal filter for nonlinear systems\([5]\). Since the observation model is nonlinear, we must apply some filter adopted for nonlinear systems.

Recently, particle filters (e.g.\([6],[7],[8],[9]\)) are often used for nonlinear systems, but we apply EKF, since state estimate is a singleton whose computation
is faster than using many estimates of particle filtering. To apply EKF, we need to compute the Jacobian matrix
\[
H(k) = \frac{\partial f}{\partial x} = \begin{bmatrix}
H_{1,1} & H_{1,2} & H_{1,3} \\
\vdots & \vdots & \vdots \\
H_{MN,1} & H_{MN,2} & H_{MN,3}
\end{bmatrix}
\] (23)
whose size is \(MN \times 3\), and the function form can be derived from equation (11) as
\[
H_{ij,1} = \frac{\partial f_{ij}}{\partial q_1} = -q_3(q_1\cos q_2 \cos \phi - q_2 \sin q_2 \cos \phi)/\beta^2
\]
\[
H_{ij,2} = \frac{\partial f_{ij}}{\partial q_2} = -q_3(q_1\sin q_2 \sin \phi_1 \cos \phi + q_2 \sin q_2 \sin \phi_1 \cos \phi)
\]
\[
H_{ij,3} = \frac{\partial f_{ij}}{\partial q_3} = 1/\beta
\]

5.2 Dealing with Mixture PDFs
Next we must decide how to deal with the mixture of PDFs. Since the case of obstacle or hole/ditch is a kind of outlier[10], a simple approach is to remove data (seem to be) generated from obstacles or holes/ditches. Hereafter, we will take an approach along this method.

5.3 Estimation of Signal Source
The reflection signal \(r_{ij}(k)\) comes from the ground with probability \(P_g\), some obstacle with probability \(P_s\) and a ditch or a hole with probability \(P_h\). After observing \(r_{ij}(k)\), these probabilities can be written as posterior probabilities
\[
P(c_{ij}(k)|m|R^{1:k}) \propto P_m(c_{ij}(k))p_m(r_{ij}(k)|R^{1:k-1})
\] (24)
where \(R^{1:k} = \{r(1),...,r(k)\}\), \(m \in \{g,s,l\}\), and \(r_{ij}(k)\) was assumed to be independent from any other set of \((i,j)\). Note that \(P_m(c_{ij}(k))\) is the prior probability and
\[
p_g \left( r_{ij}(k)|R^{1:k-1} \right) = N \left( \hat{f}_{ij}(k|k-1), \hat{H}_{ij}(k|k-1)P(k|k-1)\hat{H}_{ij}^T(k|k-1)+\sigma^2 \right)
\] (25)
\[
p_s \left( r_{ij}(k)|R^{1:k-1} \right) = \begin{cases} 
1 & \text{if } 0 < r_{ij}(k) \leq \hat{f}_{ij}(k|k-1) \\
0 & \text{otherwise}
\end{cases}
\] (26)
where
\[
\hat{H}_{ij}(k|k-1) = [H_{ij,1} H_{ij,2} H_{ij,3}]q=q(k|k-1)
\] (27)
and \(\hat{f}_{ij}(k|k-1)\) is the element of Jacobian of equation (23) using the predicted state value \(\hat{q}(k|k-1)\). Also,
\[
p_l \left( r_{ij}(k)|R^{1:k-1} \right) = \begin{cases} 
1 & \text{if } f_{ij}(q(k|k-1)) \leq r_{ij}(k) \leq r^* \\
0 & \text{otherwise}
\end{cases}
\] (28)
where \(r^*\) is the assumed maximum range. If we apply these PDFs to relation
\[
P(c_{ij}(k) = g|R^{1:k}) > P(c_{ij}(k) = s|R^{1:k})
\]
and
\[
P(c_{ij}(k) = g|R^{1:k}) > P(c_{ij}(k) = l|R^{1:k})
\]
we have the interval
\[
c_1(k) \leq r_{ij}(k) \leq c_2(k)
\]
with some constant \(c_1(k)\) and \(c_2(k)\).

5.4 Treatment of Detected Objects
Here we will explain how to treat the case when the observation \(r_{ij}(k)\) was judged to be a source from some object above the ground level or from some place below the ground level.

When \(P(c_{ij}(k) = g|R^{1:k}) < P(c_{ij}(k) = s|R^{1:k})\) or \(P(c_{ij}(k) = g|R^{1:k}) < P(c_{ij}(k) = l|R^{1:k})\), the signal \(r_{ij}(k)\) is considered not to be reflected from the ground surface.

Since equation (11) was derived by assuming that \(r_{ij}(k)\) came from the ground level, current \(r_{ij}(k)\) may be significantly smaller or larger than \(f_{ij}\). Thus we must weaken the effect of this observation for estimating the unknown state variables from the observation data. This is the problem of robust estimation[10], and the author developed the simultaneous estimation of the state and unknown system parameters in [11],[12] for linear systems. Our current problem also includes some unknown parameters (covariance, etc.), but, for the simplicity of the problem, we focus on the state estimation scheme, since the problem itself is much complicated in our current problem.

As we demonstrated in [11], it is possible to estimate the state based on the non-probabilistic. But there may not be sufficient data for this, we take an approach to exclude the data that were judged to be from the non-probabilistic source of signals as[12].

Here we describe the approach in more detail. Suppose that \(r_{ij}^*\) (k) was judged to be an outlier for some \(ij\). Then this observation as well as the non-linear function \(f_{ij}^*(k)\) is eliminated from the observation model (15). This corresponds to eliminating the \(i^*j^*\)-th element from the observation vector and also eliminating \(i^*j^*\)-th row from matrix \(H\). The reduced matrices are expressed with superscripts *.

5.5 Algorithm
(1) Set initial values:
\[
\hat{q}(0|0) = q, P(0|0) = P_0
\]
\[k := 1\]
(2) Time update:
Empirically, we define the parameters as follows.

\[ \dot{q}(k|k-1) = \dot{q}(k-1|k-1) \]  
\[ P(k|k-1) = P(k-1|k-1) + Q(k-1) \]  
\[ \hat{r}'_{ij}(k|k-1) = f_0^i|_x - q(k|k-1) \]  
\[ \hat{H}'^{*}(k) = H'^{*}(k) - \hat{q}(k|k-1) \]

(3) Observation update:

\[ K^{*}(k) = P(k|k-1) \hat{H}^T(k) \times [\hat{H}^*(k)P(k|k-1)\hat{H}^T(k) + R(k)]^{-1} \]
\[ = [P^{-1}(k|k-1) + \hat{H}^T(k)R^{-1}(k)\hat{H}^*(k)]^{-1} \]
\[ \times \hat{H}^T(k)R^{-1}(k) \]

Estimate \( c_{ij}(k) \) by

\[ \text{arg} \max_{m \in \{g,s,l\}} P(c_{ij} = m|R^{k,k}) \]
\[ \dot{q}(k|k) = \dot{q}(k|k-1) + K^{*}(k)[r^{*}(k) - \hat{r}^{*}(k)] \]
\[ P(k|k) = P(k|k-1) - K^{*}(k)\hat{H}^{*}(k)P(k|k-1) \]

where \( I(k) \) is a diagonal matrix consisting of 1 or 0 based on

\[ I_{ij,ij} = \begin{cases} 1, & \text{if } c_{ij}(k) = g \\ 0, & \text{otherwise} \end{cases} \]

\[ k := k + 1 \]

and, matrices or vectors with superscript * denotes that corresponding rows or columns with \( I_{ij}(k) = 0 \) are eliminated from the whole size matrices or vectors.

The reformed Kalman gain (equation (36)) requires a smaller size of matrix inversion than that of equation (35). Also, \( R^{-1}(k) \) does not need to be computed as its size, since it is a diagonal matrix. Note that this transformation cannot be applied to the Unscented Kalman Filter (UKF)[13].

5.6 Parameter Values

The parameters must be defined according to the real system. If the sensor is attached to a walking person, we define the parameters as follows.

Since \( \bar{x} = [\bar{a} \ \bar{b}]^T \), \( \alpha \) is 20° × \( \pi/180 \) rad if the sensor is attached to a belt of the body, \( \bar{b} \) is 0 rad, and \( \bar{h} \) is the height of the sensor position of the standing person (e.g. 800 mm).

The determination of the covariances is more difficult. The uncertainty of the dynamics can be determined by considering the amount of movement in one discrete time. In our experiment, the frame rate is around 10 fps, which is 100 ms. The change of \( \alpha \) is e.g. 5°. If this value is treated as the standard deviation, the variance is \( q_\alpha = (5\pi/180)^2 \). Similarly, \( q_\phi = (5\pi/180)^2 \), \( q_h = 20^2 \text{mm}^2 \).

The observation noise is due to the lens distortion. Empirically, we define

\[ R(k) = \text{diag}(\sigma^2, \sigma^2, \cdots, \sigma^2) \]

where \( \sigma^2 = 10^2 \).

6. Experimental Results

In all the experiments in this section, the values were set to \( P_g = 0.6 \), \( P_s = 0.3 \), \( P_l = 0.1 \). These are rough values that seem appropriate for our experiment site.

6.1 Static Experiments

Figure 5 shows a snapshot of the monitor of the system. We can see two image windows. The right large window shows the camera image superimposed with the detection results. Points judged to be higher than the ground surface is indicated by red color, and those judged to be lower than the ground surface is indicated by blue color. Points whose depth values unavailable are indicated by white color.

![Monitor image of this system](image.png)
area is from 15 cm to 50 cm, and the right area is the same. The bottom line is the sensor position, and the top line is 4m away. The height of one square box corresponds to 50 cm in the floor map. In this case, there are obstacles whose nearest points are between 50 cm and 100 cm in the center and the right. In the left, the obstacle is a little far. Note that, beyond obstacles, it is usually impossible to detect objects. So, in this state map, the white area beyond the red area is not necessarily flat.

6.2 Dynamic Experiments

6.2.1 On a mobility scooter

Figure 6 shows the transition of the estimated $\alpha, \psi, h$ with the sensor attached to the basket (see Fig. 1). It was recorded when it ran on the corridor of the second floor of #13 building of Konan University.

The estimated values were stable, except at the middle of the time. This is when the driver turned by the handlebar. By the structure of the mobility scooter, the rotation angle $\psi$ changed substantially. At the same time, the center of the handlebar ($h$) becomes low when turning. Moreover, the depression angle $\alpha$ becomes large.

6.2.2 Radio gymnastics No.1

Figure 7 shows the transition of the estimated $\alpha, \psi, h$ with the sensor attached to a human body doing radio gymnastics No.1 of NHK.

We can notice that the height changed as the person bended his knees by 8 times at the early stage of this gymnastics. Following that, he tilted his body to left (minus angle), right (plus angle), left and right, twice at each time. After that, he bended his body deeply forward to touch the ground. It can be found by looking at the large values of depression angle. However, the system wrongly took the ground points and hence the estimate of height took very large values wrongly. This system is not designed to work properly when the view has almost no ground points.

6.2.3 Walking person

Figure 8 shows the transition of the estimated $\alpha, \psi, h$ with the sensor attached to a walking person’s front waist in a narrow corridor in a private house.

When he was walking, he faced the wall several times. However, the vaqules of the posture were properly estimated constantly.

6.3 Comparison with Other Algorithm

Here we demonstrate the results of different algorithms. In Figs.9 and 10, the left window shows the result with the proposed algorithm based on state-space approach, and the right window shows the one with the algorithm based on optimization algorithm explained in Section 3. Both algorithms work well in most cases, but they showed some different properties in the cases where the view includes walls or some large high obstacles. Figure 9 shows a result near a wall. The posture of the sensor deviated from the true one. Figure 10 shows a result near stairs.

By the same reason, the problem in the optimization-based approach appears.

By the state-space based approach, the transition speed can be controlled by the state update model.

7. Conclusions

In this paper, the state space model of the data captured by depth sensors has been developed, where the three unknown parameters of the posture of the mobile object was included in the state vector. By applying EKF, the real-time estimation scheme was successful, where the off-ground points were excluded in the observation points for the state-estimation scheme.

The depth sensor of this kind intrinsically is not able to capture data from the direct sunlight, but danger situation such as obstacle or ditch can be detected relatively well even in such environment, because of shaded objects can be detected.

This system can be applied to navigation of elderly people or blind people. In the application stage that should follow this research, it is necessary to pay a lot of attention to the safety for humans.
The parameters in this model, i.e. $P_g$, $P_s$, $P_l$, $\sigma^2$, $c_1$ and $c_2$ have not been tuned sufficiently. It will be our future work to consider how to decide or identify these parameter values.

Acknowledgements

This work was partially supported by JSPS Grant-in-Aid for Scientific Research #24500288, and also supported by MEXT, Japan.

This paper is a revised and expanded version of the paper “State Estimation of Depth Sensor’s Posture Attached to an Unstable Dynamic Object” included in the proceedings of SSS’12.

References


**Author**

Masahiro Tanaka (Member)

Masahiro Tanaka was born in May, 1956. He graduated from the Department of Applied Mathematics and Physics, Kyoto University in 1979, got his MEng. in 1981 and Dr. Eng. in Control Engineering in 1990 from Kyoto University. From 1981, he was with Shimadzu Corporation, Shiga University, Okayama University, and since 1999, he has been a full professor at Konan University, Kobe, Japan, where he is currently at Department of Intelligence and Informatics. His scientific fields include soft computing, computer vision, image processing, state estimation, robotics and visual sensor applications. He is a member of SICE, IEEE, SOFT, RSJ and IEE.