A Method for Tracking On-body Sensor Positions Utilizing Prior Knowledge

Naoto Migita
Kyushu Institute of Technology
1-1 Sensui-cho, Tobata
Kitakyushu, 804-8550, JAPAN
n.migita96@gmail.com

Sozo Inoue
Kyushu Institute of Technology
1-1 Sensui-cho, Tobata
Kitakyushu, 804-8550, JAPAN
sozo@mns.kyutech.ac.jp

Takuya Yumiyama
Kyushu Institute of Technology
1-1 Sensui-cho, Tobata
Kitakyushu, 804-8550, JAPAN
takuya.yumiyama@gmail.com

Takeshi Nishida
Kyushu Institute of Technology
1-1 Sensui-cho, Tobata
Kitakyushu, 804-8550, JAPAN
nishida@cntl.kyutech.ac.jp

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Abstract
In this research, we aim at estimating the positions and directions of on-body mobile devices such as smartphones with accelerometers and gyroscopes. We propose a method utilizing prior knowledge of positions and directions of sensors. We model the prior knowledge by neighborhood method trained from a motion capturing system, and combine with physical principles by Bayes' theorem. To assess our approach, we developed a system for collecting acceleration and position data using an accelerometer and motion capture, and experimented with data obtained using it. In contrast to the conventional method, the experimental result shows that the proposed method stably follows a trajectory.

Author Keywords
Smartphone, Accelerometers, Gyroscopes, Tracking On-Body Sensor Positions

ACM Classification Keywords
I.4.8 [Scene Analysis]: tracking.

Introduction
Recently, activity recognition with sensor data has become realistic by the spread of mobile devices such as smartphones with accelerometers and gyroscopes. In this research, we aim at estimating the positions and

directions of on-body mobile devices such as smartphones with accelerometers and gyroscopes. In the literature, many researches for recognizing several types of activities exist in which the activities are represented in categorical variable, but few tackle with numeric ones, that is the positions and directions of sensors on the body.
Since the sensors output differential values, estimating the positions and directions corresponds to the integrated values, which is challenging under noises. In this paper, we propose a method utilizing prior knowledge of positions and directions of sensors. If the device is on the body, we can assume the the positions and the directions have specific distributions. We model them by neighborhood method trained from a motion capturing system, and combine with physical principles by Bayes' theorem.
To assess our approach, we developed a system for collecting acceleration and position data using an accelerometer and motion capture, and experimented with data obtained using it. In contrast to the conventional method, the experimental result shows that the proposed method stably follows a trajectory.
In this paper, we firstly formulate the physical principles of positions, directions, and sensor values of mobile devices, and describe the conventional estimation and proposed method. In addition, we present an approach for collecting acceleration and position data. Finally, a basic assessment of the system is provided.

Related Work

Recently, the introduction of inexpensive motion capture systems such as Microsoft Kinect has opened up a new line of active research [1, 2]. Kinect is used to estimate the human pose from the depth image. We note that there are methods that can estimate the position and orientation of sensors using portable sensors and cameras [4], and can detect faster movements with higher accuracy than motion capture using a wearable wristband device that combines aaccelerometers and gyroscopes [5]. In our research, we aim to estimate the human pose more easily using only accelerometers instead of Kinect. In addition, research is carried out to convert data between Kinect and IMU (Inertial Measurement Units) [3]. IMU is a device for measuring the movement of a person from a sensor attached to the joint. We use Kinect in our research too. However, our work differs from the previous research in the manner in which prior distributions are modeled.
In robotics area, there are many methods to estimate positions and orientations using prior knowledge [6–8]. We use prior knowledge to estimate positions and orientations too. However, the estimation target of our research is different from them.

Formulation

In this chapter, we describe the formulation of the stated quantity of the mobile device.

Coordinate system of the mobile device

We define a world coordinate system as Σ, and a coordinate system fixed to mobile devices as Σ_D. Fig. 1 shows these relationships.

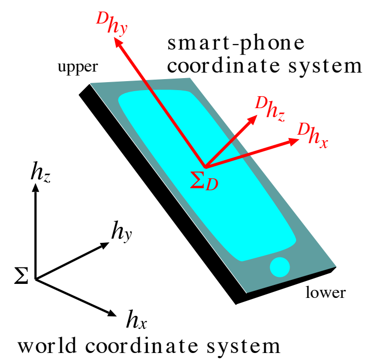

Figure 1: Phone coordinate system.

Further, the state vectors are defined as follows.

$$\boldsymbol{h}_k \triangleq \begin{bmatrix} h_{x,k} & h_{y,k} & h_{z,k} \end{bmatrix}^T \in \Sigma$$
$$\boldsymbol{s}_k \triangleq \begin{bmatrix} s_{x,k} & s_{y,k} & s_{z,k} \end{bmatrix}^T \in \Sigma$$
$$\boldsymbol{a}_k \triangleq \begin{bmatrix} a_{x,k} & a_{y,k} & a_{z,k} \end{bmatrix}^T \in \Sigma$$
$$\boldsymbol{\theta}_k \triangleq \begin{bmatrix} \theta_{x,k} & \theta_{y,k} & \theta_{z,k} \end{bmatrix}^T \in \Sigma$$
$$\boldsymbol{\phi}_k \triangleq \begin{bmatrix} \phi_{x,k} & \phi_{y,k} & \phi_{z,k} \end{bmatrix}^T \in \Sigma$$

Here, x, y and z are coordinate axes, and k is discrete time. Further, $\boldsymbol{h}_k$, $\boldsymbol{s}_k$ and $\boldsymbol{a}_k$ are the location of the center of gravity, velocity and acceleration of mobile devices, respectively. Moreover, $\boldsymbol{\theta}_k$ and $\boldsymbol{\phi}_k$ are the rotation angular velocity and the rotation angle of Σ_D to Σ respectively. $\boldsymbol{h}_0$, $\boldsymbol{s}_0$, $\boldsymbol{a}_0$, $\boldsymbol{\phi}_0$ and $\boldsymbol{\theta}_0$ are assumed to be known.

Relationship of State Quantity

Angular velocity and acceleration of mobile devices are to be measured at sampling intervals ∇[s]. First, the angular velocity of mobile devices in Σ is observed by the gyroscope of mobile devices.

$$^{D}\boldsymbol{\phi}_k = \boldsymbol{\phi}_k + \boldsymbol{v}_k \tag{1}$$

Here, the left shoulder D of each variable represents that the definition belongs to Σ_D. $\boldsymbol{v}_k \sim \mathcal{N}(0, \sigma_v^2)$ is a distribution that models observation noise. $\boldsymbol{v}_k$ is the average value of 0 and represents that it follows a Gaussian distribution of the dispersion σ_v^2. Next, acceleration is observed as follows by an accelerometer mounted on mobile devices as follows.

$$^{D}\boldsymbol{f}_k =^{D} \boldsymbol{a}_k +^{D} \boldsymbol{g}_k + \boldsymbol{w}_k \tag{2}$$

$\boldsymbol{w}_k$ is the observation noise follow a certain distribution. When $\boldsymbol{R}(\boldsymbol{\theta})$ is defined as the Rotation matrix with Euler angles $\boldsymbol{\theta}$ and $\boldsymbol{g}$ is defined as the invariant gravitational acceleration in k, the following equation is satisfied.

$$^{D}\boldsymbol{a}_k = \boldsymbol{R}(\boldsymbol{\theta}_k) \cdot \boldsymbol{a}_k \tag{3}$$
$$^{D}\boldsymbol{g}_k = \boldsymbol{R}(\boldsymbol{\theta}_k) \cdot \boldsymbol{g} \tag{4}$$

Further, the velocity and positions of the center of gravity of mobile devices, and the change of angle can be approximated using the Euler method by backward difference as follows.

$$\boldsymbol{s}_k = \boldsymbol{s}_{k-1} + \nabla \cdot \boldsymbol{a}_k \tag{5}$$
$$\boldsymbol{h}_k = \boldsymbol{h}_{k-1} + \nabla \cdot \boldsymbol{s}_k \tag{6}$$
$$\boldsymbol{\theta}_k = \boldsymbol{\theta}_{k-1} + \nabla \cdot \boldsymbol{\phi}_k \tag{7}$$

A Method for Tracking Holding Position of the Mobile Device

In this chapter, based on the formulation stated previously, a method for tracking the holding position of mobile devices is proposed. In essence, we describe a method for estimating $\boldsymbol{h}_k$ when angular velocity ${}^D\boldsymbol{\phi}_k$ and acceleration ${}^D\boldsymbol{f}_k$ are observed given that $\boldsymbol{h}_{k-1}$, $\boldsymbol{s}_{k-1}$ and $\boldsymbol{\theta}_{k-1}$ are known. In the following, we present an overview of the proposed and conventional methods.

Tracking the holding position of the mobile device using the conventional method:

1. Estimate acceleration $\boldsymbol{a}_k$ from angle $\boldsymbol{\theta}_{k-1}$ and the observations ${}^D\boldsymbol{f}_k$, ${}^D\boldsymbol{\phi}_k$ by linear regression.

2. Estimate value of the displacement from acceleration estimated $\boldsymbol{a}_k$ and the displacements in the past $\boldsymbol{h}_{k-1}$, $\boldsymbol{h}_{k-2}$ by double integration.

Tracking the Holding Position of the Mobile Device using the Proposed Method:

1. Collect L neighbor samples $(\boldsymbol{h}^l_{k-1}, \boldsymbol{h}^l_{k-2})$ of displacements in the past displacements $(\boldsymbol{h}_{k-1}, \boldsymbol{h}_{k-2})$ from the training data that relate to displacement.

2. Calculate $\boldsymbol{a}^l_k$ for the samples $(\boldsymbol{h}^l_k, \boldsymbol{h}^l_{k-1}, \boldsymbol{h}^l_{k-2})$ in each the sample l by calculating the difference between two times the displacements.

3. Estimate the observed values ${}^D\boldsymbol{f}^l_k$, ${}^D\boldsymbol{\phi}^l_k$ and the angle $\boldsymbol{\theta}^l_{k-1}$ by performing a linear regression for $\boldsymbol{a}^l_k$ in each sample l.

4. Estimate $\boldsymbol{h}_k$ by the k-neighborhood method for the observation values $(\boldsymbol{\theta}_{k-1}, {}^D\boldsymbol{f}_k, {}^D\boldsymbol{\phi}_k)$ using the training data for L $(\boldsymbol{\theta}^l_{k-1}, {}^D\boldsymbol{f}^l_k, {}^D\boldsymbol{\phi}^l_k)$.

Mobile Device State Estimation using the Conventional Method

Assuming that the angular velocity ${}^D\boldsymbol{\phi}_k$ and acceleration ${}^D\boldsymbol{f}_k$ have been observed in $\boldsymbol{h}_{k-1}$, $\boldsymbol{s}_{k-1}$, and $\boldsymbol{\theta}_{k-1}$ states in which a is known. At this time, displacement $\boldsymbol{h}_k$, velocity $\boldsymbol{s}_k$ and angular velocity $\boldsymbol{\theta}_k$ at time k can be derived analyticallwy in the following manner.
By substituting the $\boldsymbol{\phi}_k$ from (1) in (7), we get

$$\boldsymbol{\theta}_k = \boldsymbol{\theta}_{k-1} + \nabla \cdot \boldsymbol{\phi}_k = \boldsymbol{\theta}_{k-1} + \nabla \cdot ({}^D\boldsymbol{\phi}_k - \boldsymbol{v}_k) \tag{8}$$

By substituting $\boldsymbol{a}_k$ from (3) and ${}^D\boldsymbol{a}_k$ from (2) in (7) in a row, we get

$$\begin{aligned}\boldsymbol{s}_k &= \boldsymbol{s}_{k-1} + \nabla \cdot \boldsymbol{a}_k = \boldsymbol{s}_{k-1} + \nabla \cdot \boldsymbol{R}^{-1}(\boldsymbol{\theta}_k) \cdot {}^D\boldsymbol{a}_k \\ &= \boldsymbol{s}_{k-1} + \nabla \cdot \boldsymbol{R}^{-1}(\boldsymbol{\theta}_k)({}^D\boldsymbol{f}_k - {}^D\boldsymbol{g}_k - \boldsymbol{w}_k) \\ &= \boldsymbol{s}_{k-1} - \nabla \cdot \boldsymbol{g}_k + \nabla \cdot \boldsymbol{R}^{-1}(\boldsymbol{\theta}_k)({}^D\boldsymbol{f}_k - \boldsymbol{w}_k)\end{aligned} \tag{9}$$

By substituting this formula in (6), It is possible to obtain the $\boldsymbol{h}_k$ neglecting noise by. However, the recurrence formula is solved as follows.

$$\boldsymbol{\theta}_k = \nabla \cdot \sum_{i=1}^{k} ({}^D\boldsymbol{\phi}_i - \boldsymbol{v}_i)$$

$$\boldsymbol{s}_k = \nabla \cdot \sum_{i=1}^{k} \boldsymbol{R}^{-1}(\boldsymbol{\theta}_i)({}^D\boldsymbol{f}_i - \boldsymbol{w}_i)$$

$$\boldsymbol{h}_k = \nabla \cdot \sum_{i=1}^{k} \boldsymbol{s}_i = \nabla^2 \cdot \sum_{i=1}^{k} \sum_{j=1}^{i} \boldsymbol{R}^{-1}(\boldsymbol{\theta}_j)({}^D\boldsymbol{f}_j - \boldsymbol{w}_j)$$

Considering only the influence of noises $\boldsymbol{v}_i$ and $\boldsymbol{w}_i$ the effect of the order of $\sum_{i=1}^{k} \boldsymbol{v}_i = O(k)$ is stored in the angular velocity $\boldsymbol{\theta}_k$ and the effect of the order of $\sum_{i=1}^{k} \sum_{j=1}^{i} \boldsymbol{R}^{-1}(\boldsymbol{\theta}_j) \cdot \boldsymbol{w}_j = O(k^2)$ is stored in the displacement $\boldsymbol{h}_k$. This makes it difficult to ensure accuracy.

Implementation of the Conventional Method
In the following, we describe the implementation of the conventional method and compare it to the proposed method as described in the next section.

Given that $\boldsymbol{h}_{k-1}$, $\boldsymbol{s}_{k-1}$ and $\boldsymbol{\theta}_{k-1}$ are known, the acceleration is observed, and the following procedures are performed.

1. Calculate acceleration $\boldsymbol{a}_k$ from $\boldsymbol{\theta}_{k-1}$ and obtain the observed values ${}^D\boldsymbol{f}_k$, ${}^D\phi_k$ as $\boldsymbol{a}_k \leftarrow \boldsymbol{\alpha}\boldsymbol{A}(\boldsymbol{\theta}_{k-1}, {}^D\boldsymbol{f}_k, {}^D\phi_k)$ by linear regression given that $\boldsymbol{\alpha}$ is the regression coefficient vector and $\boldsymbol{A}$ is a function defined by $\boldsymbol{A}(\boldsymbol{\theta}, \boldsymbol{f}, \boldsymbol{\phi}) = \boldsymbol{R}(\boldsymbol{\theta} + \nabla\boldsymbol{\phi})\boldsymbol{f}$.
2. Ealculate the estimate of the displacement
$$\boldsymbol{h}_k \leftarrow 2\boldsymbol{h}_{k-1} - \boldsymbol{h}_{k-2} + \nabla^2\boldsymbol{a}_k$$
from $\boldsymbol{a}_k$ as determined, $\boldsymbol{h}_{k-1}$ and $\boldsymbol{h}_{k-2}$.

The derivation of these equations is as follows.

- $\boldsymbol{a}$ in step **1**, by (2)-(4),
$$\begin{aligned}\boldsymbol{a}_k &= \boldsymbol{R}^{-1}(\boldsymbol{\theta}_k)^D\boldsymbol{a}_k \\ &= \boldsymbol{R}(-\boldsymbol{\theta}_k)({}^D\boldsymbol{f}_k - {}^D\boldsymbol{g}_k - \boldsymbol{w}_k) \\ &= \boldsymbol{R}(-\boldsymbol{\theta}_k)({}^D\boldsymbol{f}_k - \boldsymbol{w}_k) - \boldsymbol{g}\end{aligned}$$
From (1) and (7)
$$\boldsymbol{a}_k = \boldsymbol{R}(-\boldsymbol{\theta}_{k-1} - \nabla({}^D\boldsymbol{\phi}_k - \boldsymbol{v}_k))({}^D\boldsymbol{f}_k - \boldsymbol{w}_k) - \boldsymbol{g}$$
$\boldsymbol{a}_k$ is modeled With the exception of the constant term and noise.

- $\boldsymbol{a}$ in step **2**, using (5)-(6),
$$\begin{aligned}\boldsymbol{h}_k &= \boldsymbol{h}_{k-1} + \nabla\boldsymbol{s}_k = \boldsymbol{h}_{k-1} + \nabla(\boldsymbol{s}_{k-1} + \nabla\boldsymbol{a}_k) \\ &= \boldsymbol{h}_{k-1} + \nabla((\boldsymbol{h}_{k-1} - \boldsymbol{h}_{k-2})/\nabla + \nabla\boldsymbol{a}_k) \\ &= 2\boldsymbol{h}_{k-1} - \boldsymbol{h}_{k-2} + \nabla^2\boldsymbol{a}_k\end{aligned}$$

Then, explaining using conditional probability.

$$P(\boldsymbol{h}_k | \boldsymbol{h}_{k-1}, \boldsymbol{h}_{k-2}, \boldsymbol{\theta}_{k-1}, {}^D\boldsymbol{f}_k, {}^D\boldsymbol{\phi}_k)$$

Using the addition theorem,

$$\begin{aligned}= \int_{\boldsymbol{a}_k} & P(\boldsymbol{h}_k | \boldsymbol{h}_{k-1}, \boldsymbol{h}_{k-2}, \boldsymbol{\theta}_{k-1}, {}^D\boldsymbol{f}_k, {}^D\boldsymbol{\phi}_k, \boldsymbol{a}_k) \\ & \cdot P(\boldsymbol{a}_k | \boldsymbol{h}_{k-1}, \boldsymbol{h}_{k-2}, \boldsymbol{\theta}_{k-1}, {}^D\boldsymbol{f}_k, {}^D\boldsymbol{\phi}_k) d\boldsymbol{a}_k\end{aligned}$$

As seen from the derivation of the above equation, we assume conditional independence between $(\boldsymbol{h}_{k-1}, \boldsymbol{h}_{k-2})$ and $(\boldsymbol{\theta}_{k-1}, {}^D\boldsymbol{f}_k)$ under $\boldsymbol{a}_k$,

$$= \int_{\boldsymbol{a}_k} P(\boldsymbol{h}_k | \boldsymbol{h}_{k-1}, \boldsymbol{h}_{k-2}, \boldsymbol{a}_k) P(\boldsymbol{a}_k | \boldsymbol{\theta}_{k-1}, {}^D\boldsymbol{f}_k, {}^D\boldsymbol{\phi}_k) d\boldsymbol{a}_k \tag{10}$$

In (10), the average of the second factor calculated using step **1** and the first factor is calculated using step **2**.

State Estimation of the Positions of On-Body Mobile Devices Utilizing Prior Knowledge
In this section, we propose a method capable of providing information to estimate the prior distributions of variables and improve the accuracy of state estimation by the neighborhood method. In advance, it should be constructed prior distribution of displacement and velocity using motion capture such as Kinect sensor. Accumulation of the noise is suppressed by giving the

estimated time it. It is assumed that $\boldsymbol{h}_{k-1}$, $\boldsymbol{h}_{k-2}$, $\boldsymbol{\theta}_{k-1}$, ${}^D\boldsymbol{f}_k$ and ${}^D\boldsymbol{\phi}_k$ are known. By Bayes theorem,

$$P(\boldsymbol{h}_k|\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2},\boldsymbol{\theta}_{k-1},{}^D\boldsymbol{f}_k,{}^D\boldsymbol{\phi}_k)$$
$$\propto P(\boldsymbol{\theta}_{k-1},{}^D\boldsymbol{f}_k,{}^D\boldsymbol{\phi}_k|\boldsymbol{h}_k,\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})P(\boldsymbol{h}_k|\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})$$

Then, from the addition theorem,

$$= \int_{\boldsymbol{a}_k} P(\boldsymbol{\theta}_{k-1},{}^D\boldsymbol{f}_k,{}^D\boldsymbol{\phi}_k|\boldsymbol{h}_k,\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2},\boldsymbol{a}_k)$$
$$\cdot P(\boldsymbol{a}_k|\boldsymbol{h}_k,\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})d\boldsymbol{a}_k$$
$$\cdot P(\boldsymbol{h}_k|\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})$$

As with the previous section, assuming conditional independence between $(\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})$ and $(\boldsymbol{\theta}_{k-1},{}^D\boldsymbol{f}_k)$ under the $\boldsymbol{a}_k$.

$$= \int_{\boldsymbol{a}_k} P(\boldsymbol{\theta}_{k-1},{}^D\boldsymbol{f}_k,{}^D\boldsymbol{\phi}_k|\boldsymbol{a}_k)P(\boldsymbol{a}_k|\boldsymbol{h}_k,\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})d\boldsymbol{a}_k$$
$$\cdot P(\boldsymbol{h}_k|\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})$$

In this formula,

- $P(\boldsymbol{\theta}_{k-1},{}^D\boldsymbol{f}_k,{}^D\boldsymbol{\phi}_k|\boldsymbol{a}_k)$ which is the first factor is obtained from $(\boldsymbol{\theta}_{k-1},{}^D\boldsymbol{f}_k,{}^D\boldsymbol{\phi}_k) = \boldsymbol{\beta}\boldsymbol{a}_k + \boldsymbol{\beta}_0$ by a linear regression. However, $\boldsymbol{\beta}, \boldsymbol{\beta}_0$ is the regression coefficient vector.
- $P(\boldsymbol{a}_k|\boldsymbol{h}_k,\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})$ which is the second factor is uniquely obtained by (5)-(6) as follows.

$$\begin{aligned}\boldsymbol{a}_k &= (\boldsymbol{s}_k - \boldsymbol{s}_{k-1})/\nabla \\ &= ((\boldsymbol{h}_k - \boldsymbol{h}_{k-1})/\nabla - (\boldsymbol{h}_{k-1} - \boldsymbol{h}_{k-2})/\nabla)/\nabla \\ &= (\boldsymbol{h}_k - 2\boldsymbol{h}_{k-1} + \boldsymbol{h}_{k-2})/\nabla^2\end{aligned}$$

- At $P(\boldsymbol{h}_k|\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})$ which is the third factor, sampling is executed by the neighborhood method. If A of one of $(\boldsymbol{h}_l,\boldsymbol{h}_{l-1},\boldsymbol{h}_{l-2})$ is sampled by preparing the training data set in advance, this distribution follows approximately follows $P(\boldsymbol{h}_k,\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})$. By utilizing this concept, the samples according to $P(\boldsymbol{h}_k|\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})$ are obtained by sampling the neighborhood of $(\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})$ from $\mathcal{H}$.

Implementation of the Proposed Method using the Neighborhood Method

In the following, we describe the implementation of the proposed method. When acceleration ${}^D\boldsymbol{f}_k$ and angular velocity ${}^D\boldsymbol{\phi}_k$ have been observed and $\boldsymbol{h}_{k-1}$, $\boldsymbol{h}_{k-2}$, $\boldsymbol{s}_{k-1}$ and $\boldsymbol{\theta}_{k-1}$ are known, this method performs the following procedure.

1. Obtain L samples $(\boldsymbol{h}^l_{k-1},\boldsymbol{h}^l_{k-2})$ in the neighborhood of the $(\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})$ and $\boldsymbol{h}^l_k$ corresponding its from learning data $\mathcal{H}$.This distribution of $\boldsymbol{h}^l_k$ follows approximately the third factor $P(\boldsymbol{h}_k|\boldsymbol{h}_{k-1},\boldsymbol{h}_{k-2})$.
2. In accordance with the second factor, alculate $\boldsymbol{a}^l_k \leftarrow (\boldsymbol{h}^l_k - 2\boldsymbol{h}^l_{k-1} + \boldsymbol{h}^l_{k-2})/\nabla^2$ for each l.
3. In accordance with the first factor, calculate $(\boldsymbol{\theta}^l_{k-1},{}^D\boldsymbol{f}^l_k,{}^D\boldsymbol{\phi}^l_k) \leftarrow \boldsymbol{\beta}\boldsymbol{a}^l_k + \boldsymbol{\beta}_0$ for each l by linear regression.
4. Obtain M samples in the neighborhood of the observed values $(\boldsymbol{\theta}_{k-1},{}^D\boldsymbol{f}_k,{}^D\boldsymbol{\phi}_k)$ from L $(\boldsymbol{\theta}^l_{k-1},{}^D\boldsymbol{f}^l_k,{}^D\boldsymbol{\phi}^l_k)$, and to determine the average
$$\frac{1}{M}\sum_m \boldsymbol{h}^m_k$$
of $\boldsymbol{h}^m_k$ corresponding to it to estimated value of $\boldsymbol{h}_k$.

Evaluation

In this chapter, we describe the data collection system and the preliminary experiments in three-dimensional space.

Data collection system

We have developed a software for collecting data in the Processing environment. Fig. 2 shows a screen image of the software.

Figure 2: A screen image of the data collection system

The value of the accelerometer is also received by the UDP communication at the same time as the position information from Kinect. This received data is stored to a file is sampled at the same time as the position information. Simultaneously, the audio and video also stored. Although our system operates at an acceleration frequency of 100 Hz, it synchronizes with Kinect, which operates at 30 Hz. We use iPodTouch as an accelerometer. Our system on the iPodTouch incorporates the HASC Logger[1], which is a toolkit for activity recognition research.

Experiment

We performed a preliminary experiment to estimate the displacement from the horizontal movement of the accelerometer with one human subject. The experiment was carried out with a right hand to the acceleration sensor. The sensor is held with the screen facing outward, that is, the left hand side of the sensor is set to be the X-axis positive velocity. After the start of the recording, the hand is moved at a slow pace in the transverse direction for approximately one min.

Setup

We estimate prior distributions from acceleration and displacement data generated by the mobile sensor and the Kinect, respectively. However, both mobile sensor and Kinect data are prone deviations caused by sampling time and the scale. However, we do not know the X-axis direction of the acceleration sensor to verify to see if it is directly perpendicular to the force of gravity. Therefore, we carried out a pretreatment the following as. We do not know the X-axis direction of the accelerometer or to see if it is perpendicular to the force of gravity exactly. Therefore, Considered easily with gravity component moving average of every second, it was smoothed (Hereinafter, this is a low-pass filter) by a weighted moving average of 9:1 of the two samples, after conducting the removal of the gravity component. Orientation information obtained from the Kinect, $\boldsymbol{s}_k$ is obtained from the position information of the hand usind (6), and $\boldsymbol{a}_k$ is obtained by (5). We used the *low-pass*

[1]HASCTool, http://hasc.jp/

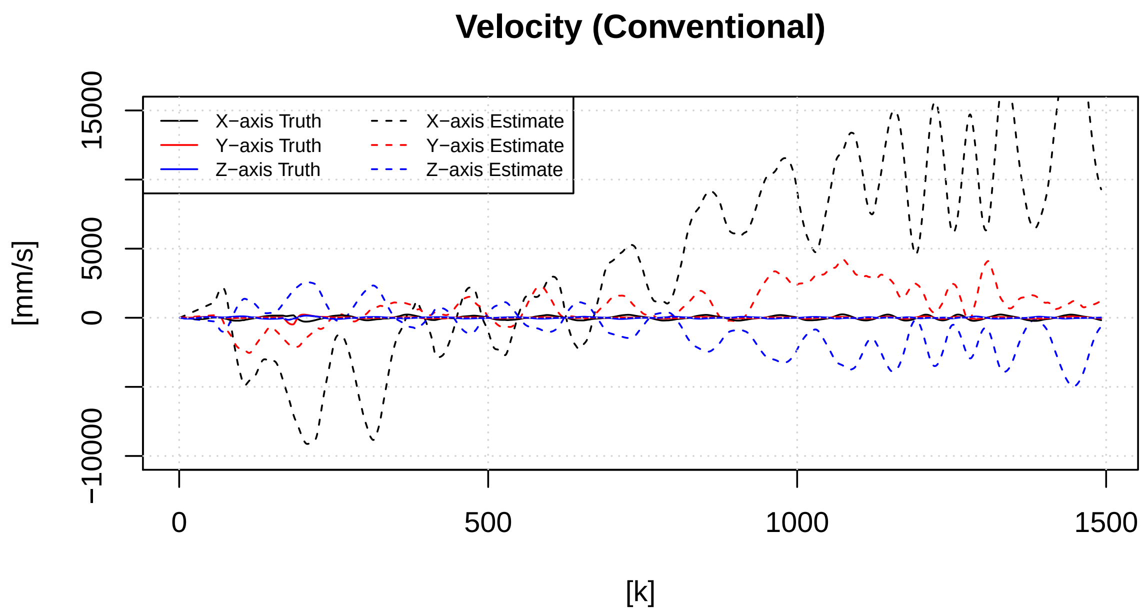

Figure 3: Estimated result of the speed according to the conventional method

filter before and after these stages. Further, we shifted the time of the accelerometers so that the cross-correlation is maximized. Moreover, in order to satisfy the assumption that $\boldsymbol{h}_{k-1}$, $\boldsymbol{h}_{k-2}$ are known, the initial value of the estimated value are aligned to $\boldsymbol{h}_1$, $\boldsymbol{h}_2$.

Building a Prior Distribution

The prior distribution of a variable is obtained from the displacement, the speed and the acceleration of Kinect. Further, the acceleration of the mobile sensor was computed as described previously. To calculate the distribution, the first half of the data were used as learning data. However, in the proposed method, L is set to 500, and M is set to 125(please see previous chapter).

Experimental Result

Fig.3 shows the estimation result using the conventional method. Fig.4 shows the estimation result obtained by the proposed method.In the conventional method, the result depicts a large displacement error. Therefore, we show a figure of the estimated result of the speed. In both figures,the X-axis represents size of the data set. The

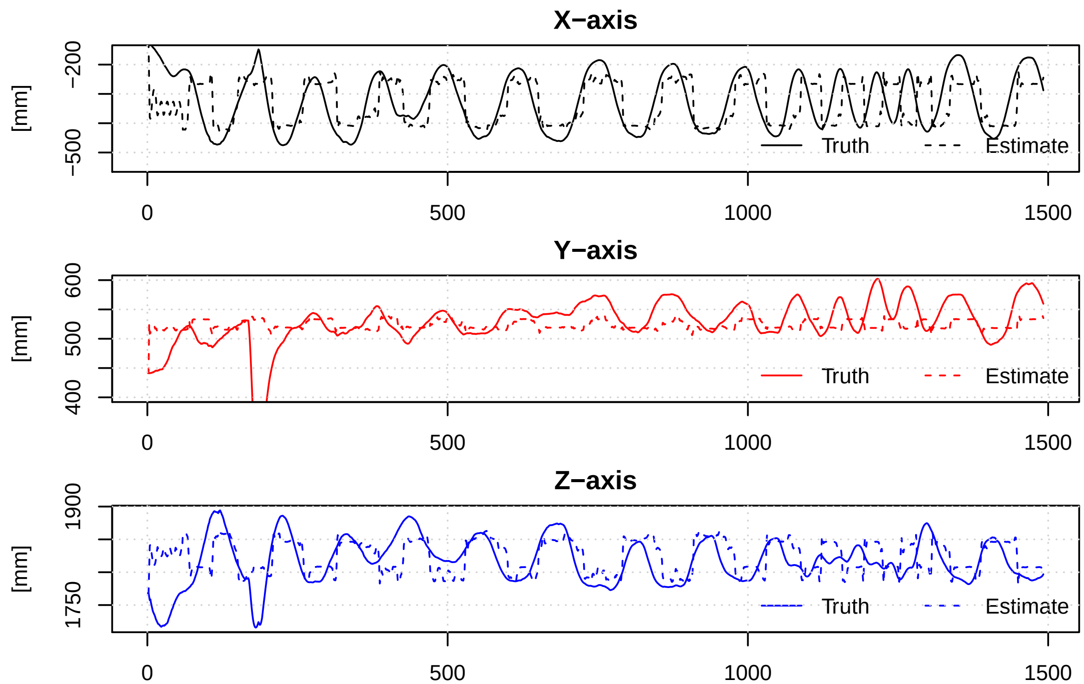

Figure 4: Estimated result of displacement by the proposed method

Y-axis in Fig.3 represents the value of the speed, whereas in Fig.4, it represents the value of displacement. In the conventional method, the predicted value (Estimate) has a large value that is significantly relative to the true value (Truth) in stage the speed. Therefore, when the displacement is considered, the misalignment width is expected to further increase. Moreover, the Fluctuation not be followed, so It cannot be said to follow well.

In the proposed method, any axes in the first half followed a certain pattern to some extent. However, signification deviations are observed near $k = 200$ at Y-axis. This discrepancy is results from the failure to utilize prior knowledge to discover major changes. The second half, although it is not able to follow to some extent to the middle, the value is the slight deviation near the end. This is because it is used for learning the first half. Moreover, the direction of the estimated value has a smaller amplitude on the whole. This is because this method calculates the average of the estimated values at the end, and therefore, it tends to yield a small estimate of the direction-amplitude. In this manner, we confirmed that the proposed method can follow in a stable in comparison with conventional methods

Conclusion

In this paper, we propose a method utilizing prior knowledge of positions and directions of sensors, and performed an initial assessment. The result shows that the proposed method stably follows a given trajectory compared to conventional methods.

The future plan is to consider high-dimensional data, and determine the accuracy of our approach. Moreover, we expect to improve the accuracy and the computational speed through the introduction of importance sampling such as a particle filter.

We use Kinect as a motion capture this time, so a phenomenon that fail to capture often happened in case of hand in front of the body. Another consideration that may be of interest is to increase the accuracy of the motion capture procedure, which we believe would be useful for modeling probability distributions. In In futureaddition, we hope to optimize the L and M parameters.

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