Simultaneous Estimation of Contact Position
and Tool Shape using an Unscented Particle Filter

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The robots used in our daily lives come in contact with the environment not only directly, but also through grasped objects and tools. In such cases, the shape of the grasped objects could be unknown or uncertain; thus, the shape must be estimated using information about the contact. However, previous studies could not estimate the shape of the grasped objects without knowledge about the contact environment. In this study, unscented particle filters were used to estimate the contact positions, contact forces, and shape of the tools, simultaneously. In addition, we verified that the proposed method can estimate these characteristics by measuring the force and torque in the robots.

Keywords: Intrinsic contact sensing, particle filter, contact position estimation, tool shape estimation

1. Introduction

Robots are expected to perform various tasks in our daily lives such as cooking, cleaning, and object manipulation. Because most of these tasks involve contact with their environment, the detection and control of the contact are important issues.

Some daily tasks involve contact with the environment through tools or grasped objects. For example, most cooking processes require the use of tools. When robots are used for cleaning a room, they need to pick up objects and place them on racks carefully. In such situations, it is necessary to know the contact positions on the tools and control the contact force using object-oriented coordinate systems.(10,11).

In many cases, the contact between the tool and the environment is invisible due to occlusions.(12,13). The contact position can be estimated through force sensing in such cases. Contact occurs only on the surface of the tools, and therefore, the robots should know the shape of the tools to estimate the contact positions. However, the tool shape is often unknown or uncertain. In such cases, the robots should be able to estimate the shape of the grasped objects.

Several research studies have focused on the estimation of the contact position and shape of objects. For example, Salisbury(14) proposed a method for identifying the contact features on an insensitive end-effector using a six-axis force/torque sensor; such methods have been applied to the whole-body force sensation of robots(15) and haptic interfaces(16). However, these methods require the exact geometry of the shape of the objects. Tsuji et al.(9) proposed a method based on the recursive least square method to estimate the contact position without the shape geometry. Karayiannidis et al.(10) proposed a method for estimating the position of the contact point and a normal vector of the contact surface. Hebert et al.(11) proposed a method to estimate the location of grasped objects in robots’ hand by fusing vision, force, and joint angle information. Mimura et al.(12) proposed methods to identify the contact parameters (contact position, degrees of freedom of contact, and contact direction) based on active force sensing.

Approaches based on the Bayesian inference have also been researched. Petrovskaia et al.(13) estimated the contact positions of robot links using a Bayesian inference. Behbahani et al.(14) proposed the idea of Haptic SLAM, which estimates the robot hand pose and object shape simultaneously. Vezzani et al.(15) proposed an object pose estimation method that employs touching the objects. Koike et al.(16) proposed an intrinsic contact sensing method, which does not require information about the geometric shape of the objects. However, these methods were not applied to the contact between the grasped objects and the environment. In such a case, the contact position cannot be measured directly, and only candidates of the contact position are estimated as a line. It is significantly different from the case wherein the tool shape is known. Therefore, a simultaneous estimation of the tool shape and contact locations remains to be achieved.

This study proposes a method to estimate the contact positions, contact forces, and shape of the tools, simultaneously, using unscented particle filters (UPFs)(17,18), which is a Monte-Carlo algorithm for Bayesian inference. Because the proposed method uses information about force and torque instead of vision and pose, this method can be used in a wide
range of situations, such as when robotic vision is unavailable and when the environment changes by touching.

The remainder of this paper is organized as follows. Section 2 explains the difficulty of the problem by taking a simple example. Section 3 introduces the generic particle filters and UPFs. Section 4 explains the proposed method. The proposed method is verified in Sects. 5 and 6. The conclusions and future work are discussed in Sect. 7.

2. Contact Position Estimation

This section explains the difficulty of contact position estimation by considering a simple case: an object is equipped on a force/torque sensor measured force $F$ and moment $M$ as follows:

$$ F = f, \quad M = q \times f. \quad \quad \quad (1) $$

By decomposing $q = q^\parallel + q^\perp$ such that $q^\parallel \parallel f$ and $q^\perp \perp f$ are satisfied, we obtain

$$ F \times M = F \times (q \times f) = F \times (q^\parallel \times f) = \|F\|^2 q^\parallel. \quad \quad \quad (2) $$

Therefore, we can estimate $q$ as

$$ q = \frac{F \times M}{\|F\|^2} + \alpha F, \quad \quad \quad (4) $$

where $\alpha$ is an unknown constant value. Equation (4) represents a line through $q$ in the same direction as $f$.

If we know the shape of the object, we can specify the contact position as the point of intersection between the line and surface of the object. However, when the shape is unknown or uncertain, we cannot specify the contact position. Although the method by (9) can estimate the contact position without information about the shape, the estimation is slow because it uses the change in measurement values over time. Therefore, estimating the shape is useful.

Because the measurement value of the force and moment only provides a line of candidates for the contact position, as described in Eq. (4), it is impossible to estimate the contact position without adding some constraints. Moreover, the shape of the object cannot be estimated from one measurement sample. We should estimate them gradually via long-term measurements. Therefore, an approach that can handle uncertainty during estimation is necessary.

3. Particle Filter

The particle filter $^{[10]}$ is an effective method for performing estimation under noisy and uncertain environments. Because this method is a Bayesian Monte-Carlo technique, it can handle uncertainty in a wide range of applications naturally. This feature is expected to be effective for the simultaneous estimation of contact position and shape, which involves considerable uncertainty, as explained in the previous section.

Here, we provide a summary of the generic particle filter and its algorithm based on (17).

3.1 State Space Model

Particle filters are based on the following nonlinear model:

$$ x_t = f(x_{t-1}, n^s_{t-1}), \quad \quad \quad (5) $$

$$ y_t = h(x_t, n^o_t). \quad \quad \quad \quad \quad (6) $$

Here, $x_t$ denotes the state variable, $y_t$ denotes the observation, $n^s_{t-1}$ is the system noise, $n^o_t$ is the observation noise, $f$ and $h$ are nonlinear functions, and $t$ is the discrete time index. In addition, hereinafter, we denote $x_0$ as $x_0 \equiv (x_0, \cdots, x_N)$.

The goal of estimation is to approximate a probability distribution $p(x_0, y_{1:t})$, that is, to estimate a sequence of states $x_0 \equiv (x_0, \cdots, x_t)$ from a given sequence of observations $y_{1:t} \equiv (y_1, \cdots, y_t)$.

3.2 Particle Approximation

For a given function $\phi$, the expectation value can be obtained as

$$ E_{x_0 \sim p(x_0|y_1)}[\phi(x_0)] = \int \phi(x_0)p(x_0|y_1)dx_0 \quad \quad \quad (7) $$

It is difficult to obtain $p(x_0|y_1)$ directly. Therefore, we define an arbitrary distribution $q(x_0|y_1)$, which is called the proposal distribution. Then, Eq. (7) can be rewritten as

$$ E_{x_0 \sim p(x_0|y_1)}[\phi(x_0)] = \int q(x_0)p(x_0|y_1)\phi(x_0)dx_0 \equiv \int q(x_0)p(x_0|y_1)\frac{\phi(x_0)}{q(x_0|y_1)}dx_0 \equiv \frac{E_{x_0 \sim q(x_0|y_1)}[\phi(x_0)]}{E_{x_0 \sim q(x_0|y_1)}[w(x_0)]} \quad \quad \quad (8) $$

where

$$ w(x_0) = \frac{p(y_1|x_0)p(x_0|y_1)}{q(x_0|y_1)} \quad \quad \quad \quad \quad (9) $$

Here, $w_i(x_0)$ is the weight for a state variable $x_0$.

If a group of particles $\{x_0^{(i)}|i = 0, \cdots, N-1\}$ can be sampled from $q(x_0|y_1)$, Eq. (8) can be approximated as

$$ E_{x_0 \sim p(x_0|y_1)}[\phi(x_0^{(i)})] \approx \frac{1}{N} \sum_{i=0}^{N-1} \phi(x_0^{(i)}) w_i \quad \quad \quad (10) $$

$\quad = \sum_{i=0}^{N-1} \phi(x_0^{(i)}) w_i \quad \quad \quad (10) $
Here,
\[
\bar{w}^{(i)}_t = \frac{w^{(i)}_t}{\sum_{i=0}^{N-1} w^{(i)}_t} \tag{11}
\]
is the normalized value of \( w^{(i)}_t \).

Finally, the expectation \( \mathbb{E}_{x_0 \sim p(x_0 | y_{1:t})} [\phi(x_0)] \) for the given function \( \phi \) can be estimated using a group of particles \( \{ x^{(i)}_0 \}_{i=0}^{N-1} \) sampled from a distribution \( q(x_0 | y_{1:t}) \).

3.3 Filtering Algorithm

As explained above, the goal is to calculate Eq. (10). To accomplish that, we need to obtain the particles \( \{ x^{(i)}_0 \} \) and weights \( w^{(i)}_t \).

Because \( q(x_0 | y_{1:t}) \) can be decomposed as
\[
q(x_0 | y_{1:t}) = q(x_0) \prod_{t=0}^{T} q(x_t | x_{0:t-1}, y_{1:t}) \tag{12}
\]
we can obtain \( \{ x^{(i)}_t \} \) from \( q(x_t | x_{0:t-1}, y_{1:t}) \).

In addition, \( w^{(i)}_t \) can be calculated from the previous weight \( w^{(i)}_{t-1} \) instead of Eq. (9) in a straightforward manner as
\[
w^{(i)}_t = w^{(i)}_{t-1} \frac{p(y_t | x^{(i)}_t) p(x^{(i)}_t | x_{0:t-1})}{q(x^{(i)}_t | x_{0:t-1}, y_{1:t})} \tag{13}
\]

Finally, the filtering algorithm is summarized as follows:

1. Sample particles \( \{ x^{(i)}_0 \}_{i=0}^{N-1} \) from a proposal distribution \( q(x_0 | x_{0:t-1}, y_{1:t}) \).
2. Update \( \bar{w}^{(i)}_t \) using Eq. (13) and Eq. (11).
3. Resample \( \{ x^{(i)}_t \} \) according to \( \bar{w}^{(i)}_t \) and reset the weights to \( \bar{w}^{(i)}_t = \frac{1}{N} \).
4. Calculate \( \mathbb{E}_{x_0 \sim p(x_0 | y_{1:t})} [\phi(x_0)] \) using Eq. (10).

An overview is illustrated in Fig. 2.

3.4 Unscented Particle Filter

In a particle filter, the choice of the proposal distribution \( q(x_t | x_{0:t-1}, y_{1:t}) \) is an important factor that affects the performance; the easiest choice is \( q(x_t | x_{0:t-1}, y_{1:t}) = p(x_t | x_{t-1}) \). Then, we can simplify Eq. (13) into \( w^{(i)}_t = w^{(i)}_{t-1} p(y_t | x^{(i)}_t) \); however, such simplification ignores the observation sequence \( y_{1:t} \).

One effective way is to represent the proposal distribution by a Gaussian distribution as
\[
q(x_t | x_{0:t-1}, y_{1:t}) = \mathcal{N}(x_t | \mu_t, S_t) \tag{14}
\]
where \( \mathcal{N}(x | \mu, S) \) indicates the probability of \( x \) under a Gaussian distribution with mean \( \mu \) and covariance \( S \). Kalman filters are commonly used to obtain \( \mu_t \) and \( S_t \) from \( x_{0:t-1} \) and \( y_{1:t} \). A particle filter using an unscented Kalman filter (UKF) can be used to represent \( \mathcal{N}(x_t | \mu_t, S_t) \) in an unscented particle filter (UPF).

4. Method

This section explains the proposed method for the simultaneous estimation of the contact position and shape of the tools.

4.1 Problem Specification

This study considers that a robot comes in contact with the environment through a rigid tool, as illustrated in Fig. 3. The robot has a six-axis force/torque sensor near the tip of the arm to measure the force and moment due to the contact on the tool. In principle, by eliminating the inertial force and gravity, it is equivalent to attaching the sensor at the tip of the arm.

In addition, the following assumptions are considered.

1. Contact occurs only at one point or the contact shape is convex. The estimation of the contact position requires the former one, while the estimation of the tool shape requires at least one of two.
2. The shape can be represented by some parameters. If the tool contacts the environment at only a certain part, it is enough to parametrize such a part. Even though complex modeling methods such as point clouds can be used, it is better to use a small number of parameters to estimate the shape rapidly.
3. The measured force and torque are caused by only the contact force. The gravity and inertial force are assumed to be eliminated from the measured values beforehand.

The first assumption is necessary for the estimated contact positions to be on the contact shape. Multiple points of contact or line/planar contact are considered as a point contact exerted at the center of pressure. Therefore, the contact positions of the multiple contact points cannot be estimated. In addition, if the tool shape is non-convex, the estimated contact position of the resultant force can be out of shape; then, shape estimation will fail.

Even if there are multiple contact points, the proposed method can be applied by representing them with a contact force being exerted at one point. Such an approximation is effective there exist needs for robots to detect one contact point that causes a large contact force in other contact points.

Fig. 2. Overview of particle filter

Fig. 3. Overview of the situation considered in this study. The robot comes in contact with the environment through a tool. A six-axis force/torque sensor is equipped on the robot
Additionally, it is considered that it does not affect the shape estimation significantly if the occurrence period of multiple contact points is short. Moreover, the change in contact conditions can be detected by the change in force/torque measurements.

The second assumption reduces the estimation cost of the shape. In many robotic tool use cases, the class of the tool (e.g., “pencil”, “knife”, “stick”, etc.) is known. Considering the common usage of the tool, the shape parameters can be designed.

As evident from the assumptions, the proposed method does not require any knowledge of the environment. Therefore, the proposed method can be used even when the contact targets are non-rigid or moving.

### 4.2 State Space Model

A state variable \( x_t \) consists of the current contact position \( q_t \in \mathbb{R}^3 \), current contact force \( f_t \in \mathbb{R}^3 \), and shape parameters of the tool \( s_t \), as follows:

\[
x_t = (q_t, f_t, s_t)
\]

where

\[
q_t = [q^x_t, q^y_t, q^z_t]^T, \quad f_t = [f^x_t, f^y_t, f^z_t]^T, \quad s_t = [s^x_t, s^y_t, s^z_t]^T
\]

Here, \( t \) indicates the current time. Because \( s_t \) is a tuple of the parameters of the tool shape, its representation depends on the situation.

In this study, it is assumed that state variables are updated using the following equations:

\[
q_t = \text{Proj}_s (q_{t-1} + n^q_{t-1}), \quad f_t = f_{t-1} + n^f_{t-1}, \quad s_t = s_{t-1} + n^s_{t-1}
\]

Here, \( n^q_t \) indicates the noise that follows Gaussian distribution; where the superscripts \( q, f, \text{ and } s \) indicate the contact position, contact force, and tool shape, respectively. \( \text{Proj}_s \) is a projection function onto the surface \( s_t \).

Equation (18) indicates the relationship between the shape parameter and contact position; the contact position occurs only on the surface of the tool. Considering that relationship, we can narrow down the shape of the tool by estimating the possible range of contact position. Conversely, we can also narrow down the contact position by estimating the shape of the tool.

The measurement value \( y_t \) consists of the force \( F_t \in \mathbb{R}^3 \) and moment \( M_t \in \mathbb{R}^3 \) measured using a force/torque sensor as follows:

\[
y_t = (F_t, M_t)
\]

where

\[
F_t = [F^x_t, F^y_t, F^z_t]^T, \quad M_t = [M^x_t, M^y_t, M^z_t]^T
\]

The observation process is modelled as

\[
F_t = f_t + n^f_t, \quad M_t = q_t \times f_t + n^M_t
\]

Here, \( n^f_t \) and \( n^M_t \) denote the observation noise, which follows a Gaussian distribution.

### 4.3 Filtering Algorithm

Because the particle filter follows the mechanism explained in Sect. 3, we need to model \( p(y_t|x_t^{(i)}) \), \( p(x_t^{(i)}|x_{t-1}^{(i)}) \), and \( q(x_t^{(i)}|x_{t-1}^{(i)}, y_{t-1}) \) in Eq. (13), which is required to implement a UPF.

The transition prior to \( p(x_t^{(i)}|x_{t-1}^{(i)}) \) is defined based on Eq. (18), Eq. (19), and Eq. (20) as follows:

\[
p(x_t^{(i)}|x_{t-1}^{(i)}) = N(q^{(i)}_t|q^{(i)}_{t-1}, \sigma^q_t)N(f^{(i)}_t|f^{(i)}_{t-1}, \sigma^f_t)N(s^{(i)}_t|s^{(i)}_{t-1}, \sigma^s_t)
\]

Here, \( N(x|\mu, \sigma^2) \) indicates the probability of \( x \) under a Gaussian distribution with mean \( \mu \) and variance \( \sigma^2 \) as follows:

\[
N(x|\mu, \sigma^2) = \frac{1}{(2\pi)^{\frac{3n}{2}} \det \text{diag}(\sigma^2)} \exp \left[ -\frac{1}{2} (x - \mu)^T \text{diag}(\sigma^2)^{-1}(x - \mu) \right]
\]

where \( \sigma^2 \) denotes the variance of the noise.

Here, the choice of variance parameters affects the convergence speed and robustness. If the variance is large, the estimation values converge rapidly, while it is easily affected by noises and local observations. In contrast, if the variance is small, the estimation will be robust against local fluctuations of observations, while its convergence will be slow. In the proposed method, setting the variance of the contact position as a large value and that of the shape parameters as a small value are preferable. In doing so, the UPF can estimate the contact position rapidly while estimating the tool shape in a stable manner.

The likelihood \( p(y_t|x_t^{(i)}) \) is defined based on Eq. (24) and Eq. (25) as

\[
p(y_t|x_t^{(i)}) = N(F_t|f^{(i)}_t, \sigma^f_t)N(M_t|q^{(i)}_t \times f^{(i)}_t, \sigma^M_t)
\]

We used a UKF to represent the probability distribution \( q(x_t|x_{t-1}, y_{t-1}) \).

In Eq. (28), \( s_t \) is not considered because the tool shape cannot be observed directly. Instead, the proposed method aims to estimate \( s_t \) through the contact position by considering that the contact position is restricted on the shape surface as in Eq. (18).

An overview of the proposed method is illustrated in Fig. 4.

### 5. Simulation

First, we evaluated the proposed method by simulations.

#### 5.1 Evaluation with a Line-shaped Object

In this simulation, the proposed method was compared to the conventional method in (9), which can estimate the contact position without tool shape using the recursive least square method. Although the conventional method can estimate the contact positions without prior knowledge and estimation of the tool shape, this method requires fluctuations in the contact force to converge the estimation. Additionally, an estimation delay due to the recursive least square method occurs. However, in the proposed method, the contact position is expected to be estimated with a short estimation delay without the necessity of fluctuations in the contact force.
It should be noted that this comparison method is the most preferable one because it has the same preliminary as the proposed method; the contact positions on tools can be estimated from force information without prior knowledge of the tool shape. Other methods in [10, 11, 13–15], in contrast, do not satisfy this property. Although a method in [16] also satisfies that preliminary, it has the same limitations as (9) because both methods estimate contact positions based minimization of the Euclidean distance between candidate lines of the contact position over time.

5.1.1 Setup We assumed a one-dimensional shape object as an example. The shape is assumed to be a line along the z-axis. Therefore, \( s_t \) can be represented by the following two parameters:

\[
    s_t = [s_x^t, s_y^t]^T, \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (29)
\]

\( s_x^t \) and \( s_y^t \) are the x and y positions of the line, respectively. The true parameters were set to \( s_t = [0.1 \text{ m}, -0.1 \text{ m}]^T \). An overview of the system is illustrated in Fig. 5.

The contact positions and forces were set to constant values that changed at intervals of one second. The values are determined randomly as follows:

\[
    q_{t}^s = s_x^s \quad [\text{m}] \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (30)
\]

\[
    q_{t}^f = s_y^f \quad [\text{m}] \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (31)
\]

\[
    q_{t}^s \sim U(-0.1 \text{ m}, 0.1 \text{ m}), \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (32)
\]

\[
    f_{t}^s \sim U(-20 \text{ N}, 20 \text{ N}), \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (33)
\]

\[
    f_{t}^f \sim U(-20 \text{ N}, 20 \text{ N}), \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (34)
\]

\[
    f_{t}^s \sim U(-40 \text{ N}, 0 \text{ N}), \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (35)
\]

Here, \( U(a, b) \) indicates a uniform distribution on the interval \([a, b]\). In this case, the contact force hardly changes. Therefore, it is difficult to determine the actual contact position without the knowledge of tool shape, as explained in Sect. 2.

A short-term measurement has large uncertainty in the contact position. Thus, this simulation is suitable to evaluate the validity of the proposed method that estimates the shape parameters and contact position gradually through long-term measurements.

The measurement values were calculated as

\[
    F_t = f_t + n_r^F, \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (36)
\]

\[
    M_t = q_t \times f_t + n_r^M, \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (37)
\]

where \( n_r^F \) and \( n_r^M \) are the Gaussian noises with standard deviations of 0.5 N and 0.05 Nm, respectively.

It is assumed that the force/torque sensor was calibrated, that is, the gravity was eliminated from the measurement values. The number of particles was set to \( N = 100 \). The sampling interval was set to 20 ms. The UPF was updated when the magnitude of the measured force was larger than 5 N.

5.1.2 Results We evaluated the proposed method with various parameters. In addition, we compared them using the conventional method in (9).

First, we evaluated the proposed method with various standard deviation (SD) parameters in UPF, \( \sigma_q \), \( \sigma_f \), and \( \sigma_s \). Figure 6 shows the root mean square errors (RMSE) after \( t = 15 \text{ s} \). Each parameter was evaluated 20 times. In the figures, large errors are cropped for legibility. The best case resulted in less than \( 1.5 \times 10^{-2} \text{ m} \) errors in the contact position and less than \( 2.0 \times 10^{-3} \text{ m} \) in the shape parameters. Force estimation resulted in low accuracy when the variance parameter of the contact force was large. In addition, as observed in the results, the variance parameters of the shape parameters were the most critical in accuracy because the estimation of contact position depends on shape estimation.

An estimation result is shown in Fig. 7. Here, \( \sigma_q = 10^{-3} \text{ m} \), \( \sigma_f = 1.0 \text{ N} \), and \( \sigma_s = 10^{-2} \text{ m} \) were used. The contact force was estimated correctly because they could be easily obtained from the measured force, as described in Eq. (24). The contact position converged near the estimated values. In addition, the shape parameters converged to true parameters as the number of contacts increased. Within 5 s of contact, the estimation errors of the shape parameters converged to less than \( 10^{-2} \text{ m} \). Finally, after \( t = 15 \text{ s} \), the estimation error in the shape parameters was \( 4.0 \times 10^{-3} \text{ m} \).

Next, we show the estimation results when the variance parameter of the shape parameters changed. Figures 8 and 9 show the estimation results with a large variance, \( \sigma_q = 10^{-4} \text{ m} \), and small variance, \( \sigma_q = 10^{-5} \text{ m} \), respectively. When the variance is large, the estimation of shape parameters converged rapidly, while the values fluctuated until the end. In contrast, when the variance is small, the estimation converged to the true values but it was slow.

5.1.3 Comparison with the Conventional Method We compared the proposed method with the conventional method using various forgetting factors \( \rho \) within \( 0 < \rho \leq 1 \). Figure 10 shows the RMSE of the contact position after \( t = 15 \text{ s} \). We evaluated each parameter 20 times. The conventional method resulted in more than \( 5 \times 10^{-2} \text{ m} \) of errors, which is more than three times of that obtained in the best...
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Fig. 6. Root mean squared errors (RMSE) of the estimation results after 15 s. The error bars indicate 95% confidence levels.

(a) Contact position
(b) Contact force
(c) Shape parameters

Fig. 7. Estimation results of the simulation. The solid curves represent the estimated values and the dashed curves indicate the true values.

Fig. 8. Estimation results of the simulation with a large variance $\sigma_s = 10^{-4}$ m. The estimation of shape parameters converged rapidly, while the estimated values fluctuated.

5.2 Evaluation with a Plane-shaped Object

5.2.1 Setup

We simulated another object that has a planar shape. It is assumed that this tool will make contact with the environment by a plane parallel to the $x$-$y$ plane. Because the plane can be identified by its $z$ coordinate, $s_t$ can be represented by a single parameter as follows:

$$s_t = s'_t,$$ \hfill (38)

$s'_t$ indicates the $z$ position of the plane. The true parameter was set to $s_t = 0.5$ m. An overview of the system is illustrated in Fig. 12.

An estimation result using the conventional method is shown in Fig. 11. Here, $\rho = 0.95$ was used. In comparing to Fig. 7, large errors were observed. In addition, an estimation delay occurred when the contact position changed. It is considered to be caused by the forgetting factor, $\rho$. Although the convergence speed can be improved by using a small $\rho$, it causes noisy estimation. That is, there exists a trade-off between the convergence speed and stable estimation in choosing $\rho$. In the proposed method, however, the convergence speed of the estimation of the contact position is controlled by $\sigma_q$, while the stable estimation is controlled by $\sigma_s$. This was achieved by the simultaneous estimation of contact position and shape parameters using UPF.

The contact positions and forces were set as follows:

$$q^*_x = 0.1 \sin(2\pi \times 0.2t) \cos(2\pi \times 0.5t) \text{ m}, \quad \cdots \quad (39)$$

$$q^*_y = 0.1 \cos(2\pi \times 0.3t) \sin(2\pi \times 0.7t) \text{ m}, \quad \cdots \quad (40)$$

$$q^*_z = s'_t \text{ [m]}, \quad \cdots \quad (41)$$

$$f^*_x = -10 \sin(2\pi \times 0.1t) \text{ N}, \quad \cdots \quad (42)$$

$$f^*_y = -20 \cos(2\pi \times 0.8t) \text{ N}, \quad \cdots \quad (43)$$

$$f^*_z = 10 \sin(2\pi \times 1.1t) \text{ N} + 10 \text{ N}, \quad \cdots \quad (44)$$
The number of particles was set to \( N = 300 \). Other settings were set to the same as Sect. 5.1.

5.2.2 Results First, we evaluated with various standard deviation parameters in UPF, \( \sigma_q, \sigma_f, \) and \( \sigma_s \). Figure 13 shows the root mean square errors (RMSE) after \( t = 7 \) s. Each parameter was evaluated 20 times. The best case resulted in less than \( 6 \times 10^{-2} \) m errors in the contact position and less than \( 1.5 \times 10^{-2} \) m errors in the shape parameters. As observed in the results, a larger \( \sigma_s \) than the case in Sect. 5.1 was preferred. Also, the estimation resulted in larger errors than that in Sect. 5.1 even considering the difference in the estimation interval and how to apply contact forces.

An estimation result is shown in Fig. 14. Here, \( \sigma_q = 10^{-3} \) m, \( \sigma_f = 1.0 \) N, and \( \sigma_s = 10^{-3} \) m were used. The contact position converged near the estimated values. Also, the shape parameters converged to true parameters within 4 s. Finally, after \( t = 5 \) s, the estimation error in the shape parameters was \( 7.0 \times 10^{-3} \) m.

Although this simulation had only a single shape parameter,
the estimation errors were larger than the case in Sect. 5.1. The reason is that most candidates of the shape intersect with a line of the candidates of the contact position provided by a pair of measured force and torque illustrated in Fig. 1. When the tool shape was a line, most shape candidates do not intersect with the line of the contact position candidates. Since the contact position should lay on the tool shape, a single line of the contact position candidates can narrow down the estimation of the tool shape. In contrast, when the tool shape was a plane, all shape candidates intersect with the line of the contact position candidates except in the case that the line was parallel to the plane. Hence, a single line of the contact position candidates cannot identify the tool shape. In summary, the performance of the shape estimation depends on the rate of shape candidates that intersect with a line of contact position candidates.

6. Experiment

To evaluate the proposed estimation method, especially the estimation of shape parameters, we conducted an experiment.

6.1 Setup

We used a knife-shaped tool, as shown in Fig. 15. The coordinate system was fixed at the center of the force/torque sensor. It is assumed that the contact occurs only on the blade edge (i.e., a line) that is along the z-axis. Although there are many lines along the z-axis, we can specify one of them using an intersection point between the line and the x-y plane, that is, the x and y coordinates. Therefore, we designed \( s_r \) as follows:

\[
{s_r} = \left[ s_r^x, s_r^y \right]^\top
\]

(45)

\( s_r^x \) and \( s_r^y \) are the x and y coordinates of the intersection point between the x-y plane and the line expressing the knife-edge, respectively. The true parameters are \( s_r = [2.3 \times 10^{-2} \text{ m}, 0.0 \text{ m}]^\top \). The parameters of the particle filter are detailed in Table 2. A human subject held the tool and made contact with the environment.

In this experiment, the contact condition is assumed to be a point contact. This assumption is justified in many cases. Even though the knife-shaped tools may contact at more than one point, the robots are often required to detect one contact point that causes a large contact force among other contact points. For example, when a robot is cutting a piece of boned meat, the robot should detect the position of the bone to avoid a blade spill. Here, two reaction forces occur; one from the bone and the other from the meat. In this case, however, the reaction force from the bone is larger than from the meat because the stiffness of bone is higher than that of meat. Therefore, this situation can be approximated as one-point contact with the bone by neglecting the reaction force from the meat as noise.

We used a six-axis force/torque sensor CFS034CA301U, supplied by Leptirino. The basic specifications of the sensors are detailed in Table 1. The sampling interval was set to 20 ms.

The force/torque sensor was calibrated in the first 10 s of the experiment. The subject was made to hold the tool and maintain the same pose without contact during the calibration. After that, the mean of the measured force and moment were eliminated as an offset of the sensor. In addition, the particle filter was updated when the magnitude of the measured force was larger than 5 N.

6.2 Results

The results of estimation are shown in Fig. 16. The contact force was estimated correctly. The
Estimation of Contact Position and Shape using UPF (Kyo Kutsuzawa et al.)

7. Conclusion

For robots to perform various tasks in our daily lives using tools, they need to estimate the tool shape to detect the contact position. This study proposed a method to estimate the contact position, contact force, and tool shape, simultaneously. The proposed method used UPF, which can handle uncertainty naturally. Because the proposed method only used the values of force and torque, it can be used when robotic vision is unavailable and when the environment changes on touch.

As future work, the proposed method will be generalized to include nonparametric shape representation.

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References


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