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Engineering Notes

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Attitude-Motion Estimation of Tumbling Objects Using Radio Frequency Identification

Hideyuki Tanaka,* Takehisa Yairi,† and Kazuo Machida‡
University of Tokyo, Tokyo 153-8904, Japan

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I. Introduction

THE major approach for solving the attitude-motion estimation problem is the image-based method, which is dependent upon feature detection by analyzing quantitative image data. The biggest problem of this approach is that the many phenomena in an orbital environment including occlusions, harsh lighting, and reflective materials can make reliable detection very difficult [1]. In contrast, we propose a novel method that uses rough qualitative information, that is, "Which aspects of the target are visible?" In our system, the observation data at a given time become a binary vector that consist of the values of 1 (visible) or 0 (invisible) for each aspect of the target. We introduce radio frequency identification (RFID) technology [2] to acquire such qualitative information. The target is assumed to have multiple RFID tags on its surface. Because each RFID tag has a certain communication area, only the RFID tag facing the observer returns its ID, which corresponds to the visible aspect. To solve the attitude-motion estimation problem, we apply a particle filter (PF) [3], which is applicable to any state-space model.

Although we have to address many issues when we implement our concept in practical space applications, the purpose of the study this time is to present a new concept for attitude-motion estimation and to demonstrate the basic performance of the estimation method. We conducted simulation experiments using simplified models and assumptions.

II. Description of the Problem

A. Task and Assumptions

The task is to estimate the attitude motion of a target relative to an observer. The target is a rigid free-floating and slowly tumbling body without any external force. The observer and the target keep a constant distance, and there is no relative translational motion between them. The surface of the object is divided into N_{ASP} regions, or "aspects," and the observer is able to observe which aspect faces it. The geometric model of the object is known, and so the observer knows which aspects are visible when given the relative attitude of the target. The principal axes of inertia (PAI) and the principal moment of inertia (MOI) of the object are known. The coordinate system of the object (i.e., the body frame) is set along the PAI, and its origin is placed at the object's center of gravity. The observation data consist of binary vectors, each of which consists of the values of 1 (visible) or 0 (invisible) for each aspect. Observation is performed sequentially for every time step $\mathrm{d}t$.

B. Use of RFID Technology

We introduce RFID technology to acquire such observation data. The target has N_{TAG} RFID tags on the surface, one for each aspect (i.e., $N_{\mathrm{TAG}} = N_{\mathrm{ASP}}$), and the observer has multiple RFID readers, which observe the target from several directions. RFID tags are passive tags powered by an external radiowave from RFID readers. Because the RFID tag has a certain communication area, only the RFID tag facing the RFID reader within a certain distance returns the ID. The communication area is modeled and known. One step of the observation is to send the request-to-send signal and to check the aspect IDs returned. The aspect that returns its ID is considered to be visible. The position and angle of each RFID tag are given. Also, relative positions of the object and the RFID readers are given.

III. Estimation Method

A. Formulation of the Problem

The estimation problem we solve is the recursive estimation of state $\boldsymbol{x}$ from observation $\boldsymbol{z}$. The state $\boldsymbol{x}$ is the attitude motion of the tumbling object, which consists of the quaternion $\boldsymbol{q} = [q_0 \quad q_1 \quad q_2 \quad q_3]^T$ and the angular-velocity vector $\boldsymbol{\omega} = [\omega_0 \quad \omega_1 \quad \omega_2]^T$. The reference coordinate system is the body frame along the PAI. The state vector $\boldsymbol{x}$ is defined as

$$\boldsymbol{x} \equiv [\boldsymbol{q}^T \quad \boldsymbol{\omega}^T]^T = [q_0 \quad q_1 \quad q_2 \quad q_3 \quad \omega_0 \quad \omega_1 \quad \omega_2]^T \tag{1}$$

The target has N_{TAG} RFID tags, and the observer has N_{READ} RFID readers. We define the observation $z_{l,m}$ as

$$z_{l,m} = \begin{cases} 1\text{: visible}, & \text{if the } m\text{th reader receives the ID of the } l\text{th tag} \\ 0\text{: invisible}, & \text{otherwise} \end{cases} \tag{2}$$

where $l = 1, 2, \ldots, N_{\mathrm{TAG}}$ and $m = 1, 2, \ldots, N_{\mathrm{READ}}$.

The observation by the mth reader is $z(m) = [z_{1,m}, \ldots, z_{N_{\mathrm{TAG}},m}]^T$. Thus, the system observation vector $\boldsymbol{z}$ is defined as

$$\boldsymbol{z} \equiv [z(1)^T, z(2)^T, \ldots, z(N_{\mathrm{READ}})^T]^T \tag{3}$$

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*Research Associate, Research Center for Advanced Science and Technology, Space Environment System, 4-6-1 Komaba, Meguro-ku.

†Associate Professor, Research Center for Advanced Science and Technology, Space Environment System, 4-6-1 Komaba, Meguro-ku.

‡Professor, Research Center for Advanced Science and Technology, Space Environment System, 4-6-1 Komaba, Meguro-ku. Member AIAA.

B. State Transition Model

The equation of state is

$$\frac{\mathrm{d}}{\mathrm{d}t}\boldsymbol{x} = \frac{\mathrm{d}}{\mathrm{d}t}\begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \\ \omega_0 \\ \omega_1 \\ \omega_2 \end{bmatrix} = \begin{bmatrix} (-\omega_0 q_1 - \omega_1 q_2 - \omega_2 q_3)/2 \\ (\omega_0 q_0 - \omega_1 q_3 + \omega_2 q_2)/2 \\ (-\omega_0 q_3 + \omega_1 q_0 - \omega_2 q_1)/2 \\ (-\omega_0 q_2 + \omega_1 q_1 + \omega_2 q_0)/2 \\ \omega_1\omega_2(I_1 - I_2)/I_0 \\ \omega_2\omega_0(I_2 - I_0)/I_1 \\ \omega_0\omega_1(I_0 - I_1)/I_2 \end{bmatrix} \tag{4}$$

where I_n ($n = 0$, 1, and 2) are the principal MOIs of the target.

C. Observation Model

Whether an aspect is visible or not is dependent on the communication between the RFID tag and each RFID reader. If the power density of the signal received by a reader is above a certain threshold, the tag ID is read. We set the approximate model of the power density P_{tag} [Eq. (5)], which depends on θ (the angle from the tag's normal vector) and r (the distance from the tag) with a constant k.

$$P_{\mathrm{tag}}(\theta, r) = k\frac{\cos\theta}{r^2}, \qquad (0 \le \theta \le \pi/2) \tag{5}$$

Using Eq. (5), we approximately obtain the power density of the lth tag's signal received by the mth reader as Eq. (6).

$$P_{l,m} = \begin{cases} K\frac{\cos\theta_{l,m}}{d_{l,m}^2}, & 0 \le \theta_{l,m} \le \pi/2 \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

where K is a constant depending on the transmitting power, system losses, etc.; and $\theta_{l,m}$ and $d_{l,m}$ are the angle and the distance between the lth tag and the mth reader, respectively. If $P_{l,m}$ exceeds a threshold P_{th}, the ID of the lth tag is read by the mth reader. Therefore, the observation $z_{l,m}$ defined in Eq. (2) is rewritten as

$$z_{l,m} = \begin{cases} 1, & \text{if } P_{l,m} \ge P_{\mathrm{th}} \\ 0, & \text{if } P_{l,m} < P_{\mathrm{th}} \end{cases} \quad (l = 1, 2, \ldots, N_{\mathrm{TAG}}, m = 1, 2, \ldots, N_{\mathrm{READ}}) \tag{7}$$

D. Particle Filter

The estimation problem in this study is the tracking problem of a system that includes strongly nonlinear and non-Gaussian processes, particularly in observation. We apply a particle filter to this problem. The PF approximation represents a continuous distribution of interest using a finite number of weighted random samples of the state vector or particles. It is a sequential Monte Carlo method that is applicable to non-Gaussian (multimode) and unknown-initial-value problems, which the Kalman filter (KF), the extended Kalman filter (EKF), and the recent unscented Kalman filter (UKF) do not address. To verify the validity of the fundamental concept of our method, we use the sampling importance resampling (SIR) filter [3], which is the most basic algorithm in the PF family.

IV. Simulation

A. Settings of the Simulation

1. Object Model

The target is a cubic object with an edge length of 0.5 m. It has the size of a microsatellite. We assume it is a slowly tumbling satellite rotating at a speed of about 1 rpm (0.8–1.2 rpm). We set the aspects of the object as shown in Fig. 1; N_{TAG} is 14. The aspect numbers 1–6 are set to the six surfaces of the cube and the rest of the aspects are set to the eight vertices of the cube. The direction of each aspect is set outward from the center of gravity to the aspect center.

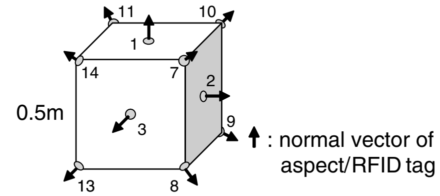

Fig. 1 Target model.

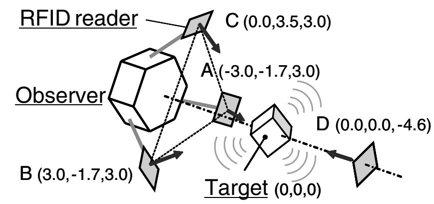

Fig. 2 Configuration of RFID readers.

2. RFID Reader Configuration

Figure 2 shows the configuration of the RFID readers, where (x, y, z) indicates the relative position of each reader from the target in meters. We assume that our system mainly uses three RFID readers (A–C), which belong to one spacecraft or a space robot used for observation. Reader D is a reader that is added as a reference for evaluation of estimation accuracy. They point at the target and observe it from a distance of 4.6 m. The target is within the communication range of passive-uhf-RFID systems.

B. Modeling of Likelihood Function

We need a likelihood function $p(\boldsymbol{z}_k|\boldsymbol{x}_k^i)$ to calculate sample weights. The likelihood $p(\boldsymbol{z}_k|\boldsymbol{x}_k^i)$ is the probability that we obtain the observation $\boldsymbol{z}_k$ when the state is $\boldsymbol{x}_k^i$. We calculate the $p(\boldsymbol{z}_k|\boldsymbol{x}_k^i)$ by forming the product of all $p_{l,m}$ such that $z_{l,m} = 1$ [Eq. (8)]. The $p_{l,m}$ is the probability that the mth reader reads the ID of the lth tag. We defined the $p_{l,m}$ as a continuous function using a logistic function [Eq. (9)], because the ideal distribution (discrete-binary distribution) leads to sample impoverishment [3].

$$p(\boldsymbol{z}_k|\boldsymbol{x}_k^i) = \prod_{z_{l,m}=1} p_{l,m} \tag{8}$$

$$p_{l,m} = \frac{B}{1 + \exp\{A[P_{\mathrm{th}} - P_{l,m}(\boldsymbol{x}_k^i)]\}} + C \tag{9}$$

where $A = 400/K$, $B = 0.98$, $C = 0.01$, and K is the constant appearing in Eq. (6). We set a threshold of $P_{\mathrm{th}} = 0.01$ K.

We do not count $p_{l,m}$ such that $z_{l,m} = 0$ [Eq. (8)], because RFID readers may fail to read RFID tags' IDs, which cannot be distinguished from cases when RFID tags are really invisible. Therefore, we ignore the information of $z_{l,m} = 0$ to improve the robustness to observation errors.

C. Simulation Results

1. Evaluation of Estimation Accuracy

We examined the estimation accuracy of our method under several conditions. The parameters are 1) the number of RFID tags N_{TAG}, 2) the number of RFID readers N_{READ}, 3) the frequency of false negatives fn, and 4) the frequency of false positives fp. We evaluated the estimation accuracy from the attitude error, which is derived from the error quaternion. Each result is the mean value of 30 trials. Estimation conditions are based on those shown in Table 1, and

Table 1 Estimation conditions

Principal MOI ratio	$[I_0 \quad I_1 \quad I_2] = [1.0 \quad 1.5 \quad 2.0]$
Observation time step	$\mathrm{d}t = 0.4$ s
Number of particles	$N_S = 2500$

Table 2 Steady-state errors (1)

	N_{TAG}	RFID tags	error, deg
case 1	6	1–6	13.19
case 2	8	7–14	11.15
case 3	14	1–14	5.65

Table 3 Steady-state errors (2)

	N_{READ}	RFID readers	Error, deg
Case 1	2	A, B	10.49
Case 2	3	A, B, C	6.64
Case 3	4	A, B, C, D	5.65

$\boldsymbol{q}$ and $\boldsymbol{\omega}$ are varied within nine random patterns. The rotational speed of the target ranges from about 0.8 to 1.2 rpm.

a. Effect of the Number of RFID Tags. Three cases for N_{TAG} are compared (Table 2). RFID tags in the table correspond to the aspect numbers shown in Fig. 1. Figure 3 shows the attitude errors for each N_{TAG}. The steady-state error is calculated by averaging the attitude error after 224 s in this case (Table 2).

Estimation accuracy improves as N_{TAG} increases. We think that this is because the expressiveness of the observation vector z increases as N_{TAG} increases; Fig. 4 shows a diagram to explain this. The observation z represents a certain region of the attitude state space. Therefore, the case of Fig. 4b has a higher resolution of attitude state space than the case of Fig. 4a, and as a consequence, the observer can more finely distinguish the difference in attitude.

b. Effect of the Number of RFID Readers. Three cases for N_{READ} are compared (Table 3). RFID readers in the table are shown in Fig. 2. The steady-state errors are shown in Table 3.

Estimation accuracy improves as N_{READ} increases. The reason for this tendency can be explained qualitatively in terms of *indeterminacy*; Fig. 5 depicts the idea schematically. The arrows showing indeterminacy indicate the possible attitude ranges around three orthogonal axes. If we use only one reader A, the possible attitude widely ranges (large indeterminacy). In fact, the attitude is completely indeterminate around the visual axis [indeterminacy (A) in Fig. 5]. This indeterminacy is reduced by observation by reader B. By integrating the information from different directions, the indeterminacy is reduced [(indeterminacy (A,B) in Fig. 5]. In the same way, indeterminacy (A,B,C) will be smaller than indeterminacy (A,B); this means an improvement in accuracy.

However, reader D seems to contribute little to improving the accuracy (the results of case 2 and case 3 are not significantly different). We think that the reason is as follows: Three readers (A–C) as a whole can observe a certain side of the target; reader D observes the opposite side. Therefore, the observation by reader D is predictable by the information provided by the other three readers, and so the information from reader D is less novel and less useful for refining the estimation. This prospect suggests that there must be a configuration in which readers can efficiently reduce each other's indeterminacy. In addition, from a practical standpoint, this result indicates that one spacecraft that is equipped with three RFID readers (A–C) is sufficient for observation in our system.

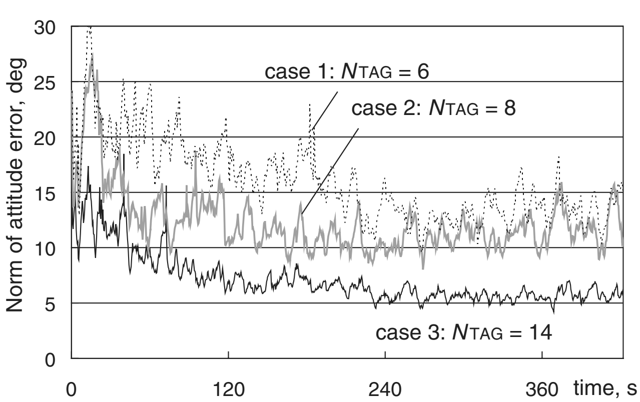

Fig. 3 Attitude-error difference for different values of N_{TAG}.

c. Effect of the Frequency of False Negatives. We use the term *false negative* as a reading error that mistakes zero (invisible) for one (visible). Such situations are likely to occur at any time of observation (e.g., occlusions of RFID tags). We examined the estimation accuracy, varying the frequency of false negatives fn for three patterns (Table 4), and the results are shown in Table 4.

The impact of false negatives is not significant. These simulations demonstrated the robustness of our method to false-negative errors such as the occlusions of RFID tags. This robustness is due to the form of the likelihood function [Eq. (8)], which neglects the information of zero (invisible).

d. Effect of the Frequency of False Positives. In contrast to false negatives, we use the term *false positive* as a reading error that mistakes one (visible) for zero (invisible). Such situations also might occur during observations under radiowave-reflective environments. We examined the estimation accuracy, varying the frequency of false positives fp for four patterns (Table 5), and the results are shown in Table 5.

The impact of false positives is not negligible. Our method is more vulnerable to false positives than to false negatives, because the likelihood function [Eq. (8)] counts the information of one (visible) without discrimination, even if it is not true. If operation under a radiowave-reflective environment is considered, our method will require some modifications so as not to count suspicious data by introducing geometrical constraints, observation histories, etc.

2. *Simultaneous Estimation with Inertial Parameters*

So far, the simulations were carried out under the condition that the MOIs of the target are known. However, this is not always the case in the real scenario of space operations. System parameters such as MOI might have been changed or may be different from known models due to various causes. We tested the estimation that estimates the attitude motion and the MOIs simultaneously.

PF is a method suitable for tracking dynamic variables, and so the estimation of static parameters is not its original usage. However, by treating parameters as time-evolving variables, the same PF framework can be used for estimation. This is the concept of the "artificial evolution" [4] of parameters. We estimate the ratio of MOIs [i.e., $I_1/I_0(=R_A)$ and $I_2/I_0(=R_B)$] with the state $\boldsymbol{x}$. R_A and R_B are used in the state transition model [Eq. (4)]. We assume that the PAI is known.

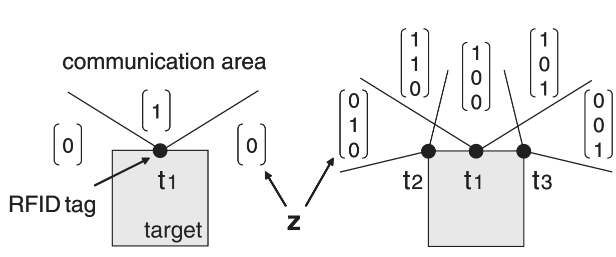

Fig. 4 Attitude-state-space division by observation vector.

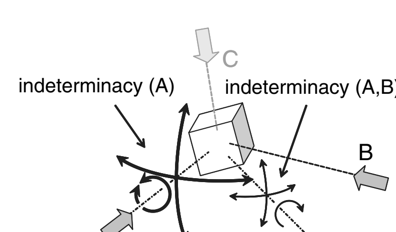

Fig. 5 Indeterminacy reduction using multiple readers.

Table 4 Steady-state errors (3)

	fn, %	Error, deg
Case 1	0	6.43
Case 2	20	7.32
Case 3	40	9.21

Table 5 Steady-state errors (4)

	fp, %	Error, deg
Case 1	0	5.67
Case 2	5	8.31
Case 3	10	12.59
Case 4	20	15.05

Figure 6 shows the result of the estimation. Simulation conditions are the same as those shown in Table 1, and $N_{\mathrm{READ}} = 4$ and $N_{\mathrm{TAG}} = 14$. The real values of R_A and R_B are 1.5 and 2.0, respectively. The steady-state error is 6.0 deg in this case. This example shows that our PF could estimate the parameters R_A and R_B and could also estimate the state.

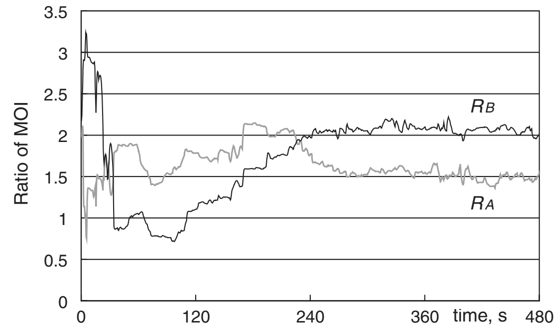

Fig. 6 Estimation of the MOI ratio.

V. Conclusions

We proposed an innovative approach for solving the attitude-motion estimation problem using only qualitative observation data. We used radio frequency identification (RFID) technology and applied a particle filter for the state estimation problem that treats strongly nonlinear models. We conducted simulation experiments under several conditions. The results showed that our method enables the accurate estimation of the attitude motion of a tumbling object and is robust to false-negative errors such as occlusions. We also checked the applicability of our estimation framework to static parameters and to state variables. Our method is not limited to only the use of RFID technology; that is, it is possible to use image data or methods of acquiring the information of visible aspects. Therefore, the method can be extended to applications using other hardware configurations. To verify the practicality of the method, experiments using real devices are needed. Then further refinement of the method to overcome obstacles in a real environment, such as false-positive errors, is desirable for real-world applications.

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