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Bayes 풍의 RFID Tag 인식

(Bayesian Cognizance of RFID Tags)

박 진 경*, 하 준*, 최 천 원**

(Jin Kyung Park, Jun Ha, and Cheon Won Choi)

요 약

하나의 reader와 여러 tag로 구성된 RFID 망에서 tag의 응답 간 충돌을 중재하기 위해 tag가 응답하도록 여러 슬롯을 마련해 주는 프레임화 및 슬롯화된 ALOHA 방식이 소개되었다. 프레임화 및 슬롯화된 ALOHA에서는 tag 인식의 효율이 극대화되기 위해 프레임 별 슬롯의 수가 최적화되어야 한다. 이러한 최적화는 tag의 수를 필요로 하나 reader는 tag의 수를 알기 힘들다. 본 논문에서는 별도로 tag의 수를 추정하지 않고 슬롯의 수에 대해 직접 Bayes action을 취하는 프레임화 및 슬롯화된 ALOHA에 기초한 tag 인식 방식을 제안한다. 구체적으로 Bayes action은 tag의 수가 갖는 사전 분포, 어떤 tag도 응답하지 않은 슬롯의 수에 대한 관찰값, 그리고 인식률을 반영한 손실 함수를 결합한 결정 문제를 풀어 구한다. 또한 tag의 수가 갖는 사전 분포의 진화를 통해 각 프레임에서 이러한 Bayes action을 지원한다. 모의 실험 결과로부터 진화하는 사전 분포와 Bayes action의 쌍은 robust 방식을 이루어 tag의 수의 참값과 초기 추측값의 큰 괴리에도 불구하고 일정 수준의 인식률을 얻을 수 있음을 관찰한다. 또한 제안하는 방식은 tag의 수에 대한 고전적인 추정값을 사용하는 방식에 비해 높은 인식 완료 확률을 얻을 수 있음을 확인한다.

Abstract

In an RFID network consisting of a single reader and many tags, a framed and slotted ALOHA, which provides a number of slots for the tags to respond, was introduced for arbitrating a collision among tags' responses. In a framed and slotted ALOHA, the number of slots in each frame should be optimized to attain the maximal efficiency in tag cognizance. While such an optimization necessitates the knowledge about the number of tags, the reader hardly knows it. In this paper, we propose a tag cognizance scheme based on framed and slotted ALOHA, which is characterized by directly taking a Bayes action on the number of slots without estimating the number of tags separately. Specifically, a Bayes action is yielded by solving a decision problem which incorporates the prior distribution the number of tags, the observation on the number of slots in which no tag responds and the loss function reflecting the cognizance rate. Also, a Bayes action in each frame is supported by an evolution of prior distribution for the number of tags. From the simulation results, we observe that the pair of evolving prior distribution and Bayes action forms a robust scheme which attains a certain level of cognizance rate in spite of a high discrepancy between the true and initially believed numbers of tags. Also, the proposed scheme is confirmed to be able to achieve higher cognizance completion probability than a scheme using classical estimate of the number of tags separately.

Keywords : RFID, tag cognizance, framed and slotted ALOHA, Bayes action, prior evolution

I. Introduction

In a contactless fashion, radio frequency identification (RFID) system attains information stored at an electronic tag by using a radio wave[1~2]. An RFID network consists of readers and tags, where a reader inquires the identities of tags and a tag responds to the reader's inquiry. In this paper, we consider an RFID network consisting of a reader and many passive tags sojourning in the vicinity of the reader as shown in figure 1. In the RFID

* 학생회원, ** 정회원, 단국대학교 공과대학 컴퓨터학부
(School of Computer Engineering, Dankook University)
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network, two or more tags may attempt to respond at the same time, which results in a collision among the tags' responses. For the reader to cognize the tags, a scheme is required to arbitrate such a collision. A framed and slotted ALOHA is one of the famous schemes of arbitrating a tag collision. It was also adopted in some standards as ISO/IEC 18000-6 Type A, ISO/IEC 18000-6 Type C, ISO/IEC 18000-7 and EPC Class 1[1~2]. In a framed slotted ALOHA, time is divided into frames and a number of slots are provided in each frame. In every frame, a tag randomly selects a slot equally likely and attempts to respond on the selected slot. In a framed and slotted ALOHA, the number of slots in a frame is an important design parameter, which affects the collision probability and the efficiency of tag cognizance as well. Research efforts were made to optimize the number of slots provided in each frame in regard to the chosen performance measure[3~7]. Such an optimization usually requires the number of tags sojourning in the neighborhood of the reader. However, the reader hardly knows it. Thus, research works tried to estimate the number of tags prior to the optimizing the number of slots in each frame[3, 5~8].

In this paper, we consider an RFID network which consists of a single reader and many tags around the reader. in such a network, we propose a tag cognizance scheme based on framed and slotted ALOHA. Previous works usually separated estimating the number of tags and determining the number of slots in each frame. In the proposed tag cognizance scheme, we first construct a decision problem which includes the prior distribution for the number of tags, the observation on the number of slots in which no tag responded and the loss function reflecting the cognizance rate, (i.e., the average number of tags that the reader cognizes per unit time). Unifying the processes of estimating the number of tags and determining the number of slots, we then take a Bayes action, (i.e., an action which minimizes the posterior expected loss), on the number of slots directly. Two measures are selected for performance evaluation; the cognizance rate and the cognizance completion probability defined as the probability that the reader cognizes the all tags. In each frame, the pair of the prior distribution and Bayes action is then compared with the pair of the classical estimate and the number of slots determined to minimizes the cognizance rate.

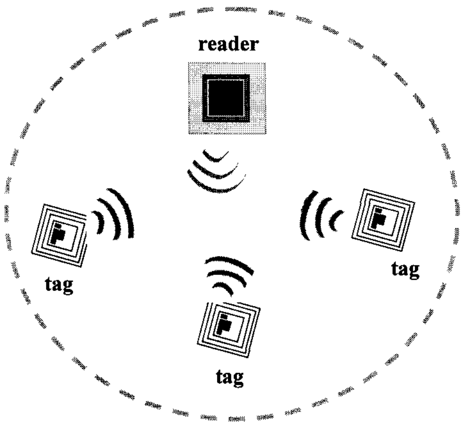

그림 1. 하나의 reader와 여러 tag로 구성된 RFID 망
Fig. 1. RFID network consisting of a single reader and many tags.

In section Ⅱ, we describe the proposed tag cognizance scheme based on framed and slotted ALOHA. In section Ⅲ, we formulate a decision problem and find a Bayes action on the number of slots. In section Ⅳ, we present an evolution of prior distribution which inspirits the sequence of Bayes actions. Section Ⅴ is devoted to the evaluation of the Bayes actions in the cognizance rate and cognizance completion probability.

Ⅱ. Tag Cognizance Scheme

In this section, we present a tag cognizance scheme based on framed and slotted ALOHA.

Figure 2 shows an exemplary frame structure in the proposed tag cognizance scheme. As shown in figure 2, a frame is divided into a part for the inquiry of the reader and a part for the responses of tags. Both of the inquiry and response parts are also divided into a number of slots. Then, the proposed

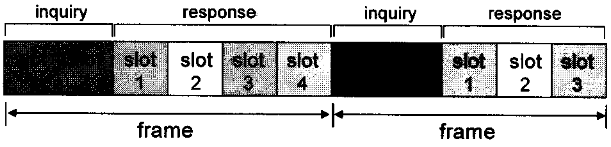

그림 2. 제안하는 tag 인식 방식에서 프레임 구조의 예
Fig. 2. Exemplary frame structure in the proposed tag cognizance scheme.

scheme behaves as follows:

1) Using the inquiry part of a frame, the reader asks the identities of tags and announces the number of slots in the response part of the frame.

2) Then, each tag selects a slot independently and equally likely among the slots in the response of the frame and responds to the reader's inquiry using the selected slot.

3) As a result, the slots in the frame are classified into three categories; slots in which no tag responded, slots in which only one tag responded and slots in which two or more tags responded simultaneously. (For later use, let X_n, Y_n, and Z_n denote the number of slots in which no tag responds, the number of slots in which only one tag responds and the number of slots in which two or more tags responds in the nth frame, respectively.) The reader then observes each slot and counts the number of slots belonging to each category.

4) Using the prior distribution for the number of tags and the observation on each slot, the reader takes a Bayes action on the number of slots in the response part of the next frame. Note that a Bayes action is chosen in the action space as to minimizes the posterior expected loss which reflects the cognizance rate.

5) Using the observation on each slot, the reader also updates the prior distribution for the number of tags.

III. Bayes Action on the Number of Slots

In this section, we find a Bayes action on the number of slots. To find such a Bayes action, we first formulate a decision problem[9]. The decision problem is a triple $(\mathcal{M}, \mathcal{A}, L)$. It consists of parameter space $\mathcal{M} = \{1,2,\cdots\}$, action space $\mathcal{A} = \{1,2,\cdots\}$ and loss function L. First, the parameter space $\mathcal{M}$ is the support of the (unknown) number of tags, denoted by M. During the nth frame for $n \in \{1,2,\cdots\}$, we a priori believe that the number of tags has the shifted Poisson distribution with parameter λ_n. Note that the prior mass for M, denoted by g_n satisfies

$$g_n(m) = \frac{e^{-\lambda_n}\lambda_n^{m-1}}{(m-1)!} \quad (1)$$

for $m \in \mathcal{M}$. Also, the prior mean of M

$$E(M) = \lambda_n + 1. \quad (2)$$

Secondly, the action space $\mathcal{A}$ is equivalent to the set of all feasible numbers that the number of slots in the response part of a frame can take. Thirdly, the value of the loss function $L(m,a)$ indicates the loss incurred by taking an action a when the true number of tags is m. In this paper, we devise a loss function as to reflect the cognizance rate, which is defined as the average number of tags cognized per unit time. Let μ_n and ν_n denote the number of slots consisting of the inquiry and response parts of the nth frame, respectively. Recall that Y_n represents the number of slots in which only one tag responds, which is equivalent to the number of tags cognized during the nth frame. Note that Y_n has the same distribution as the number of boxes filled with only one ball when M indistinguishable balls are equally likely put into ν_n boxes[10]. Thus, we have the conditional mass for Y_n for given $M = m$ as follows:

$$P(Y_n = y \mid M = m) = \frac{(-1)^y \nu_n! m!}{y! \nu_n^m} \times \sum_{j=y}^{\min\{\nu_n, m\}} \frac{(-1)^j (\nu_n - y)^{m-j}}{(j-y)!(\nu_n - j)!(m-j)!} \quad (3)$$

for $y \in \{0,\cdots,\nu_n\}$. Using the mass in (3), for example, we can obtain the conditional expectation of Y_n as

$$E(Y_n \mid M=m) = m(1-\frac{1}{\nu_n})^{m-1} \quad (4)$$

Let $\xi_{n+1}(m,\nu_{n+1})$ denote the cognizance rate during the $(n+1)$st frame. Then, we have

$$\xi_{n+1}(m,\nu_{n+1}) = \frac{m}{\mu_{n+1}+\nu_{n+1}}(1-\frac{1}{\nu_{n+1}})^{m-1} \quad (5)$$

for given $M=m$. Reflecting the cognizance rate on the loss function, we set the loss incurred by taking an action a when the true number of tags is m to be

$$L(m,a) = -\frac{m}{\mu_{n+1}+a}(1-\frac{1}{a})^{m-1} \quad (6)$$

for $m \in \mathcal{M}$ and $a \in \mathcal{A}$.

Recall that X_n represents the number of slots in which no tag responded in the nth frame. Note that X_n has the same distribution as the number of boxes with no ball when M indistinguishable balls are equally likely put into ν_n boxes [10]. Let f_n denoted the conditional mass for X_n given $M=m$. Then, we have

$$f_n(x \mid m) = \frac{\nu_n!}{x!\nu_n^M}\sum_{j=0}^{\nu_n-x}\frac{(-1)^j(\nu_n-x-j)^M}{j!(\nu_n-x-j)!} \quad (7)$$

for $x \in \{0,\cdots,\nu_n\}$. Let h_n denote the posterior mass for M, i.e., the conditional mass for M for given $X_n=x$. Using the prior mass g_n and conditional mass f_n, we obtain

$$h_n(m \mid x) = \frac{f_n(x \mid m)g_n(m)}{\sum_{k=1}^{\infty} f_n(x \mid k)g_n(k)} = \frac{\frac{e^{-\lambda_n}\lambda_n^{m-1}}{(m-1)!}}{\binom{\nu_n-1}{x}e^{\frac{\lambda_n}{\nu_n}x}(1-e^{\frac{\lambda_n}{\nu_n}})^{\nu_n-x-1}} \times \sum_{j=0}^{\nu_n-x}\binom{\nu_n}{x}\binom{\nu_n-x}{j}(-1)^j(\frac{\nu_n-x-j}{\nu_n})^m \quad (8)$$

for $m \in \mathcal{M}$.

The posterior expected loss is the expected loss with respect to the posterior distribution. From the posterior mass h_n in (8), we calculate the posterior expected loss incurred by action a, denoted by $\rho_n(h_n,a)$, as follows:

$$\begin{aligned}\rho_n(h_n,a) &= E(L(M,a) \mid X_n=x) \\ &= \sum_{m=1}^{\infty} L(m,a)h_n(m \mid x) \\ &= -\frac{[1+\frac{\lambda_n}{\nu_n}(1-\frac{1}{a})]e^{-\frac{\lambda_n}{\nu_n}\frac{\nu_n-x}{a}}}{\mu_{n+1}+a} \times [\frac{1-e^{-\frac{\lambda_n}{\nu_n}(1-\frac{1}{a})}}{1-e^{-\frac{\lambda_n}{\nu_n}}}]^{\nu_n-x-1} \\ &\quad -\frac{\frac{\lambda_n}{\nu_n}(1-\frac{1}{a})(\nu_n-x-1)e^{-\frac{\lambda_n}{\nu_n}\frac{\nu_n-x}{a}}}{(\mu_{n+1}+a)(1-e^{-\frac{\lambda_n}{\nu_n}})} \times [\frac{1-e^{-\frac{\lambda_n}{\nu_n}(1-\frac{1}{a})}}{1-e^{-\frac{\lambda_n}{\nu_n}}}]^{\nu_n-x-2}\end{aligned} \quad (9)$$

for $a \in \mathcal{A}$. A Bayes action is defined as an action which minimizes the posterior expected loss. Let a_n^*

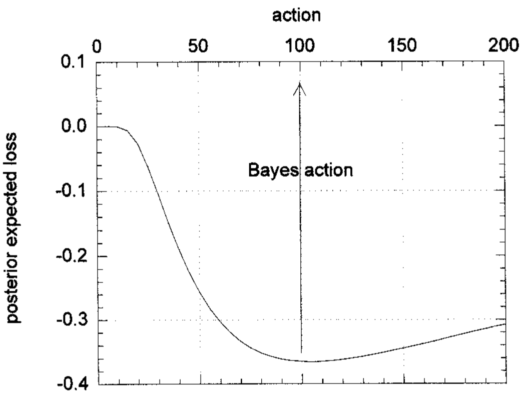

그림 3. 제안하는 tag 인식 방식에서 프레임 구조의 예
Fig. 3. Exemplary frame structure in the proposed tag cognizance scheme.

denote a Bayes action on the number of slots in the response part of the $(n+1)$st frame. Then,

$$\rho_n(h_n, a_n^*) \le \rho_n(h_n, a) \qquad (10)$$

for all $a \in \mathcal{A}$. Unfortunately, no closed form of a Bayes action is available. A numerical method may be employed to obtain a Bayes action.

Figure 3 shows the posterior expected loss $\rho_n(h_n, a)$ incurred by an action a. In this figure, we set $\lambda_n = 120$, $\nu_n = 100$, $x = 50$, and $\mu_{n+1} = 1$. In figure 3, we observe that there is a Bayes action a_n^* minimizing the posterior expected loss, which is around 100.

Ⅳ. Prior Evolution

As frames go by, the reader has more experience of observing the number of slots belonging to each category. Such an experience enables to update the prior distribution for the number of tags more precisely. Recall that g_n is the prior mass for the number of tags that we believe during the nth frame. Then, the prior evolution is defined as the sequence $\{g_n, n=0,1,\cdots\}$ of prior masses for the number of tags. Note that g_n is the mass of the shifted Poisson distribution with parameter λ_n. Using the observation on X_n, we then update g_n to g_{n+1}, (i.e., the prior mass for the number of tags that we believe during the $(n+1)$st frame), which is also the mass of the shifted Poisson distribution. The parameter of the mass with parameter λ_{n+1}. We set g_{n+1} to be the mass g_{n+1}, denoted by λ_{n+1}, is designed to satisfy the relation with the posterior mean of the number of tags in the nth frame as follows:

$$\lambda_{n+1} = E(M \mid X_n = x) - 1$$

$$= \frac{\frac{\lambda_n}{\nu_n}\left(\nu_n - x - e^{-\frac{\lambda_n}{\nu_n}}\right)}{1 - e^{-\frac{\lambda_n}{\nu_n}}} \qquad (11)$$

for $n \in 1, 2, \cdots\}$.

Ⅴ. Performance Evaluation

In this section, we evaluate the performance of the proposed tag cognizance scheme in cognizance rate and cognizance completion probability by a simulation method. In the evaluation, the proposed scheme is compared with four schemes, which are characterized by separately estimating the number of tags and then determining the number of slots as to maximize the short-term cognizance rate. These schemes are identified as ideal, Quan's, Schoute's, and Vogt's schemes. The estimate of a scheme distinguishes it from others. The ideal scheme assumes that the reader knows the number of tags exactly while others adopt classical estimates introduced in [6, 8] and [7], respectively. The simulation environment is as follows:

1) A simulation is repeated 500 times.
2) Each simulation persists until 2000 slots.
3) The inquiry part of each frame always consists of a single slot.
4) In each simulation, the true number of tags independently and identically has the shifted Poisson distribution with parameter 99.
5) No noise interferes with the response of a tag except the responses of other tags, if any.

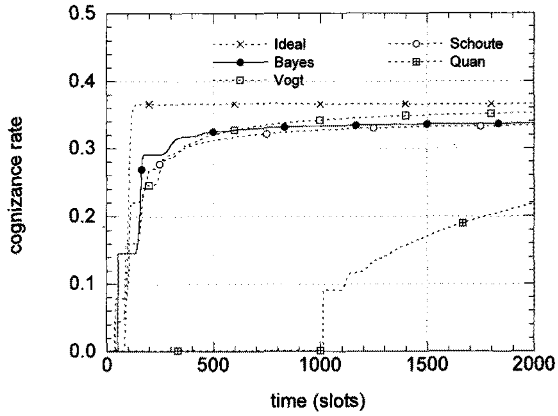

그림 4. 시간의 흐름에 따른 인식률의 추세
Fig. 4. Tendency of cognizance rate with respect to time.

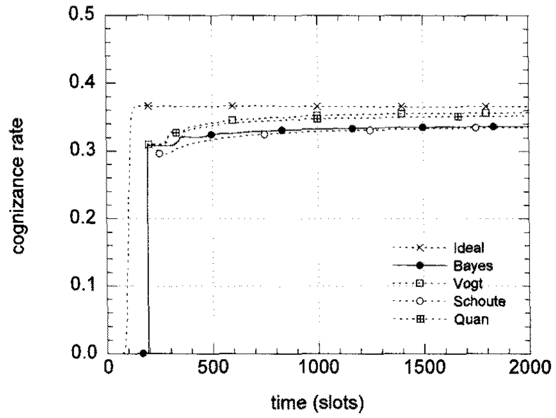

그림 5. 시간의 흐름에 따른 인식률의 추세
Fig. 5. Tendency of cognizance rate with respect to time.

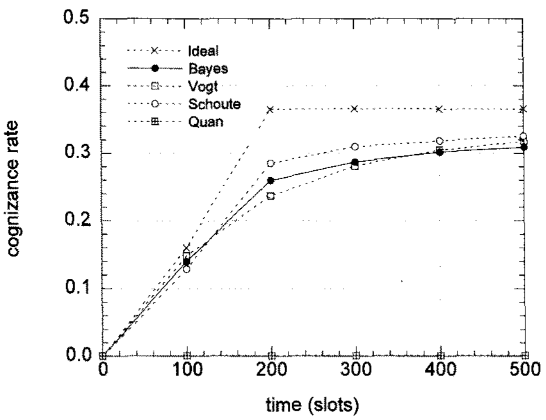

그림 6. 시간의 흐름에 따른 인식률의 추세
Fig. 6. Tendency of cognizance rate with respect to time.

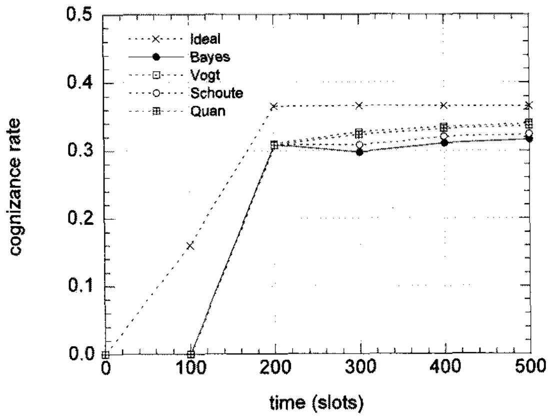

그림 7. 시간의 흐름에 따른 인식률의 추세
Fig. 7. Tendency of cognizance rate with respect to time.

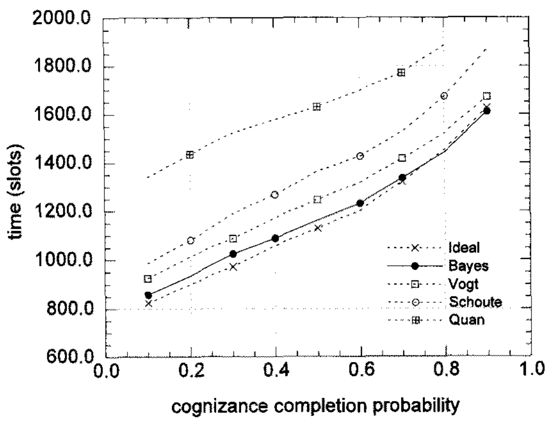

그림 8. 일정 수준의 인식 완료 확률을 얻기 위한 평균 시간
Fig. 8. Average time to attain a level of cognizance completion probability.

Figures 4 and 5 show the tendency of the cognizance rate as time goes by. Initially, the number of tags is believed to be 10 in figure 4 while it is to be 190 in figure 5. In both of the figures, the ideal scheme shows dominantly superior cognizance rate. The cognizance rate of each other scheme also seems to converge to a value, which is not significantly lower than the value to which the cognizance rate of the ideal scheme converges.

Figures 6 and 7 magnify an early part of figures 4 and 5, respectively. In figure 6, we observe that the proposed scheme is able to make the cognizance rate reach a certain high level in a relatively early time. As stated in figure 4, the number of tags is initially believed to be 10, which is highly smaller than the true number 100. As a result, a small number of slots are provided in the response part of the first frame and tags' responses collide in many slots. In such a situation, a classical estimate often falls in underestimating the number of tags, which deteriorates the efficiency of tag cognizance. In figure 7, we notice that the proposed scheme performs as similarly as other schemes in cognizance rate. As stated in figure 5, the number of tags is initially believed to be 190, which is larger than the true number 100. In such a situation, a classical estimate behaves in a relatively precise way. From these two

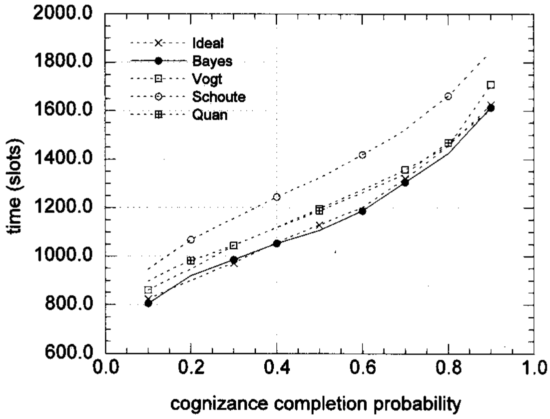

그림 9. 일정 수준의 인식 완료 확률을 얻기 위한 평균 시간
Fig. 9. Average time to attain a level of cognizance completion probability.

figures, we confirm that the sequence of Bayes actions forms a robust scheme which attains a certain level of cognizance rate in spite of a high discrepancy between the true and initially believed numbers of tags.

Figures 8 and 9 show the average time needed to attain a certain level of cognizance completion probability. As in figures 4 and 5, the number of tags is initially believed to be 10 in figure 8 while it is to be 190 in figure 9. To attain a certain level of cognizance completion probability, we observe that the proposed scheme needs a shorter average time than other schemes. The phenomenon is partially due to the robustness of the proposed scheme against the discrepancy between the true and initially believed numbers of tags.

VI. Conclusions

In an RFID network consisting of a reader and many tags, we proposed a tag cognizance scheme based on framed and slotted ALOHA. In a framed slotted ALOHA, it is desirable to determine the number of slots to enhance the efficiency of tag cognizance, which requires the information about the number of tags. For such a determination, the proposed scheme distinctively takes a Bayes action on the number of slots directly without estimating the number of tags separately, where a Bayes action is found by solving a decision problem which incorporates the evolving prior distribution for the number of tags, the observation on the number of slots in which no tag responded and the loss function reflecting the cognizance rate. From the simulation results, we observed that the proposed scheme is robust enough to attain a certain level of cognizance rate in spite of a high discrepancy between the true and initially believed numbers of tags. Also, the proposed scheme was confirmed to produce higher cognizance completion probability than a scheme using a classical estimate of the number of tags separately.

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저자 소개

박 진 경(학생회원)
2002년 단국대학교 대학원 정보통신학과 석사.
2009년 현재 단국대학교 대학원 전자컴퓨터공학과 박사 과정.
<주관심분야 : 매체 접근 제어, 무선망, 큐잉 이론>

최 천 원(정회원)
1986년 서울대학교 공과대학 전자공학과 학사.
1988년 서울대학교 대학원 전자공학과 석사.
1996년 University of California at Los Angeles 전기공학과 박사.
현재 단국대학교 공과대학 컴퓨터학부 교수
<주관심분야 : 매체 접근 제어, 오류 제어, 무선망, 큐잉 이론>

하 준(학생회원)
2002년 단국대학교 대학원 전자컴퓨터공학과 석사.
2009년 현재 단국대학교 대학원 전자컴퓨터공학과 박사 과정.
<주관심분야 : 데이타 트래픽 모형화, 무선망, 큐잉 이론>