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RFID 망에서 Tag 인식을 위한 회고풍의 최대 우도 결정 규칙

(Retrospective Maximum Likelihood Decision Rule for Tag Cognizance in RFID Networks)

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요 약

Tag가 reader 주변을 정상적으로 오가는 별 형태의 RFID 망을 고려한다. 이 RFID 망에서 주위의 tag를 인식하기 위해 동적으로 프레임에 속한 슬롯의 수를 결정하는 동적 프레임화 및 슬롯화된 ALOHA 기반의 방식을 제안한다. 이 tag 인식 방식은 특징적으로 주위의 tag의 기대 수를 추정하기 위해 R-회고풍 최대 우도 규칙이라 불리는 규칙을 채택하여 이전 R 개의 프레임에서 얻은 관찰 값을 tag의 기대 수의 우도를 최대화하는 과정에 사용한다. 모의 실험 결과는 회고의 깊이를 조금 늘려도 인식 성능이 유의할 만큼 향상됨을 보여준다.

Abstract

We consider an RFID network configured as a star in which tags stationarily move into and out of the vicinity of the reader. To cognize the neighboring tags in the RFID network, we propose a scheme based on dynamic framed and slotted ALOHA which determines the number of slots belonging to a frame in a dynamic fashion. The tag cognizance scheme distinctively employs a rule for estimating the expected number of neighboring tags, identified as R-retrospective maximum likelihood rule, where the observations attained in the R previous frames are used in maximizing the likelihood of expected number of tags. Simulation result shows that a slight increase in depth of retrospect is able to significantly improve the cognizance performance.

Keywords: RFID, tag cognizance, ALOHA, maximum likelihood rule, cognizance rate

Ⅰ. Introduction

Radio frequency identification (RFID) is a system where a reader, in a contactless fashion, attains the information stored at an electronic tag by using a radio wave[1~2]. In this paper, we consider an RFID network configured as a star such that a single reader is located in the middle of the crowd of tags. In an RFID network, a reader hardly knows about the tags in its vicinity. Thus, the reader must cognize the neighboring tags prior to attaining the information stored at a tag. To cognize a tag, the reader usually broadcasts the inquiry about the identities of tags and each tag makes response to the inquiry. In an RFID network configured as a star, two or more tags may attempt to respond at the same time, which results in a collision among the tags' responses. For arbitrating a collision which takes place in the tag cognizance process, tag cognizance schemes based on framed and slotted ALOHA were proposed and adopted in some standards[1~2]. In a tag cognizance scheme based on framed and slotted ALOHA, time is divided into

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frames and a number of slots are provided in each frame. Then, each tag randomly selects a slot in the frame and attempts to respond using the selected slot. In the scheme, the number of slots provided in a frame highly affects the tag cognizance performance. Naturally, efforts were made to determine the number of slots in an optimal fashion. Such an optimal design were also performed in two directions; statically[3~5] and dynamically[6~11]. A dynamic design typically needs the information about the number of tags around the reader. However, the reader hardly knows it. Thus, various rules for estimating the number of tags were proposed in the previous works [6]-[8]. Most of them, however, use the observation attained only in the present frame to determine the number of slots provided in the next frame. Furthermore, tags are assumed to move neither into nor out of the vicinity of the reader while the tag cognizance proceeds.

In this paper, we consider an RFID network configured as a star in which tags with low degree of mobility move into or out of the vicinity of the reader in a stationary fashion. In the RFID network, we propose a tag cognizance scheme based on dynamic framed and slotted ALOHA. The proposed scheme is characterized by its employment of a rule for estimating the expected number of neighboring tags, identified as R-retrospective maximum likelihood rule, where the observations attained in the R previous frames are used in maximizing the likelihood of expected number of tags. Also, the proposed scheme determines the number of slots provided in the next frame so as to maximize the short-term cognizance rate during the next frame. The proposed scheme is then evaluated by measuring the long-term cognizance rate.

In section Ⅱ, we present a tag cognizance scheme based on dynamic framed and slotted ALOHA. In section Ⅲ, we introduce an R-retrospective maximum likelihood rule for estimating the expected number of tags in the vicinity of the reader. In section Ⅳ, we determine the number of slots in a frame as to maximize the short-term cognizance rate. Section Ⅴ is devoted to the evaluation of the proposed tag cognizance scheme.

Ⅱ. Tag Cognizance Scheme: Overview

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

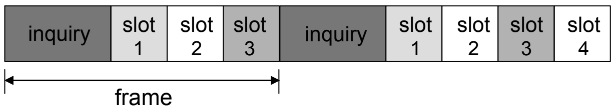

그림 1. 제안한 tag 인식 방식에서 사용되는 시간 구조
Fig. 1. Time structure in proposed tag cognizance scheme.

Figure 1 shows an exemplary time structure employed by the proposed tag cognizance scheme. Time is divided into frames and a frame is again divided into a part for the inquiry of the reader and a part for the responses of tags. Also, each of the inquiry and response parts consists of a number of slots which have a fixed duration time. Using the above time structure, the reader cognizes the tags in its vicinity as follows:

(1) At the start of each frame, the reader inquires the identities of tag and announces the number of slots in the response part of the frame by using the inquiry part.

(2) Each tag equally likely chooses a slot in the response part of the frame and responds to the reader's inquiry using the selected slot.

(3) Looking at each slot in the response part of the frame, the reader dichotomically decides whether no tag responded in the slot or not.

(4) If the reader decides that at least one tag responded in a slot, the reader tries to cognize a tag in the slot.

(5) Using the observation on the number of slots in which no tag responded, the reader estimates the expected number of tags in its vicinity. (For details, see section 3.)

(6) Using the estimate of the expected number of

tags, the reader determines the number of slots in the response part of the next frame as to maximize the short-term cognizance rate during the next frame. (For details, see section 4.)

III. Estimation of Expected Number of Tags

In the RFID network, a tag is assumed to have mobility. As time goes by, some tags may leave the region in which the reader is physically able to cognize tags while new tags may enter the region. Let M_n denote the number of tags sojourning in the vicinity of the reader at the start of the nth frame. Then, we assume that $\{M_n, n=1,2,\cdots\}$ is a strictly stationary sequence such that M_n has the Poisson distribution with unknown parameter λ, i.e., for all $n \in \{1,2,\cdots,\}$

$$P(M_n = m) = \frac{e^{-\lambda}\lambda^m}{m!} \tag{1}$$

for $m \in \{0,1,\cdots\}$.

As shown in figure 1, a frame consists of inquiry and response parts. Let A_n and B_n denote the numbers of slots in the inquiry and response parts of the nth frame, respectively, for $n \in \{1,2,\cdots\}$. Upon the inquiry about the identities of the tags in the nth frame, each of the M_n tags independently and equally likely chooses a slot among the B_n slots and responds. Then, the reader measures the power level at each slot and decides whether no tag responded or not.

Let X_n represent the number of slots where the reader decides that no tag responded during the nth frame. Then, the length of the response part B_n is completely determined by use of the observation on $X_1, \cdots, X_{n-1}$. Assume that the reader makes no error in deciding whether no tag responded or not. Then, the random variable X_n is equal to the number of slots in which no tag responds during the nth frame. Thus, X_n has the same distribution as the number of boxes filled with no ball when M_n indistinguishable balls are equally likely put into B_n boxes[12]. Therefore, when the number of tags $M_n = m$, the random variable X_n has the following conditional mass for given $X_1 = x_1, \cdots, X_{n-1} = x_{n-1}$.

$$\begin{aligned} &P(X_n = x_n | X_1 = x_1, \cdots, X_{n-1} = x_{n-1}, M_n = m) \\ &= \sum_{j=0}^{B_n - x_n} \binom{B_n}{x} \binom{B_n - x_n}{j} (-1)^j \left(1 - \frac{x_n + j}{B_n}\right)^m \end{aligned} \tag{2}$$

for $(x_1, \cdots, x_n) \in \{0, \cdots, B_1\} \times \cdots \times \{0, \cdots, B_n\}$ and $m \in \{0,1,\cdots\}$. Since the number of tags M_n has the Poisson distribution with parameter λ, X_n has the conditional mass for given $X_1 = x_1, \cdots, X_{n-1} = x_{n-1}$ as follows:

$$\begin{aligned} &P(X_n = x_n | X_1 = x_1, \cdots, X_{n-1} = x_{n-1}) \\ &= \sum_{m=0}^{\infty} P(M_n = m) \\ &\cdot P(X_n = x_n | X_1 = x_1, \cdots, X_{n-1} = x_{n-1}, M_n = m) \\ &= \binom{B_n}{x_n} \phi_n^{x_n} (1 - \phi_n)^{B_n - x_n} \end{aligned} \tag{3}$$

for $(x_1, \cdots, x_n) \in \{0, \cdots, B_1\} \times \cdots \times \{0, \cdots, B_n\}$, where

$$\phi_n = e^{-\frac{\lambda}{B_n}}. \tag{4}$$

Also, the joint mass for $X_1, \cdots, X_n$ is calculated to be

$$\begin{aligned} &P(X_1 = x_1, \cdots, X_n = x_n) \\ &= \prod_{k=1}^{n} \binom{B_k}{x_k} \phi_k^{x_k} (1 - \phi_k)^{B_k - x_k} \end{aligned} \tag{5}$$

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

At the start of a frame, the reader is assumed to have the information that the number of neighboring tags has a Poisson distribution with parameter λ. However, the reader does not know the true value of the parameter λ. To determine the length of the next frame in an optimal fashion, the reader thus has to estimate the parameter λ precisely. For this purpose, we propose a R-retrospective maximum likelihood rule for estimating the parameter λ as follows. Let $f_n^{(R)}$ denote the joint mass for X_{n-R+1}, $\cdots$, X_n given X_1, $\cdots$, X_{n-R}. Then,

$$\begin{aligned} & f_n^{(R)}(x_{n-R+1},\cdots,x_n \mid x_1,\cdots,x_{n-R}) \\ &= P(X_{n-R+1}=x_{n-R+1},\cdots,X_n=x_n \\ &\quad \mid X_1=x_1,\cdots,X_{n-R}=x_{n-R}) \\ &= \frac{P(X_1=x_1,\cdots,X_n=x_n)}{P(X_1=x_1,\cdots,X_{n-R}=x_{n-R})} \\ &= \prod_{k=n-R+1}^{n}\binom{B_k}{x_k}\phi_k^{x_k}(1-\phi_k)^{B_k-x_k} \end{aligned} \tag{6}$$

for $(x_1,\cdots,x_n)\in\{0,\cdots,B_1\}\times\cdots\times\{0,\cdots,B_n\}$.

Suppose that the reader observes $X_k=x_k$ for $k\in\{1,\cdots,n\}$. Define

$$\begin{aligned} & d_n^{(R)}:\{0,\cdots,B_{n-R+1}\}\times\cdots\times\{0,\cdots,B_n\} \\ & \rightarrow(0,\infty) \end{aligned} \tag{7}$$

to be a function such that the joint mass $f_n^{(R)}(x_{n-R+1},\cdots,x_n \mid x_1,\cdots,x_{n-R})$, which is in fact the likelihood of the parameter λ [13], is maximized by setting $\lambda=d_n^{(R)}(x_{n-R+1},\cdots,x_n)$ for $n\in\{1,2,\cdots\}$. Then, $d_n^{(R)}$ is identified as the R-retrospective maximum likelihood rule for estimating the parameter λ. For $R=1$, the R-retrospective maximum likelihood rule is easily calculated to be

$$d_n^{(1)}(x_n)=B_n\log\left(\frac{B_n}{x_n}\right) \tag{8}$$

if $x_n\in\{1,\cdots,B_n\}$. For $R\in\{2,3,\cdots\}$, however, the R-retrospective maximum likelihood rule is not obtained in an explicit form. Taking the logarithm on the likelihood in (6) and differentiating it, we have the equation

$$\sum_{k=n-R+1}^{n}\frac{\phi_k}{1-\phi_k}=\sum_{k=n-R+1}^{n}\frac{x_k}{B_k}\frac{1}{1-\phi_k} \tag{9}$$

where $\phi_k=e^{-\frac{\lambda}{B_k}}$ for $k\in\{1,2,\cdots\}$. Then, a solution of the equation in (9) is the value of the R-retrospective maximum likelihood rule $d_n^R(x_{n-R+1},\cdots,x_n)$.

Ⅳ. Determination of Length of Response Part

Let Y_n represent the number of tags that the reader cognizes during the nth frame. Recall that the inquiry and response parts in the nth frame consist of A_n and B_n slots, respectively. Then, the short-term cognizance rate during the nth frame is defined to be

$$\rho_n=\frac{E(Y_n \mid X_1=x_1,\cdots,X_{n-1}=x_{n-1})}{A_n+B_n} \tag{10}$$

for $n\in\{1,2,\cdots\}$. Using (10), we determine the length of the response part in the next frame to maximize the short-term cognizance rate during the next frame.

Suppose that the reader cognizes a tag during a slot if and only if only the tag responds during the slot. Then, Y_n is equal to the number of slots in which only one tag responds. Recall that M_n tags sojourn in the vicinity of the reader at the start of the nth frame and the response part of the nth frame consists of B_n slots. Then, Y_n has the same distribution as the number of boxes filled with only one ball when M_n indistinguishable balls are equally likely put into B_n boxes [12]. Thus, when the number of neighboring tags $M_n=m$, the random variable Y_n has the following conditional mass for given $X_1=x_1$, $\cdots$, $X_{n-1}=x_{n-1}$.

$$\begin{aligned} & P(Y_n=y_n \mid X_1=x_1,\cdots,X_{n-1}=x_{n-1},M_n=m) \\ &= \frac{(-1)^{y_n}B_n!m!}{y_n!B_n^m} \\ &\cdot\sum_{j=y_n}^{\min\{B_n,m\}}\frac{(-1)^j(B_n-j)^{m-j}}{(j-y)!(B_n-j)!(m-j)!} \end{aligned} \tag{11}$$

for $y_n\in\{0,\cdots,\min\{B_n,m\}\}$. The conditional expectation of Y_n may be directly calculated by use of the conditional mass in (11). Also, it can be obtained by introducing some random variables. For $j \in \{1, \cdots, B_n\}$, let V_j indicates that only one tag responds in the jth slot of the response part in the nth frame, i.e., $V_j = 1$ if only one tag responds in the jth slot and $V_j = 0$ otherwise. Then, we have

$$Y_n = \sum_{j=1}^{B_n} V_j. \tag{12}$$

Since only one tag among the all M_n tags must respond in the jth slot for V_j to be 1, we have

$$\begin{aligned} & E(V_j \mid X_1 = x_1, \cdots, X_{n-1} = x_{n-1}, M_n = m) \\ & = P(V_j = 1 \mid X_1 = x_1, \cdots, X_{n-1} = x_{n-1}, M_n = m) \\ & = \binom{m}{1} \left(\frac{1}{B_n}\right)^1 \left(1 - \frac{1}{B_n}\right)^{m-1} \end{aligned} \tag{13}$$

for all $j \in \{1, \cdots, B_n\}$. Since the number of neighboring tags has the Poisson distribution with parameter λ, we thus obtain

$$\begin{aligned} & E(Y_n \mid X_1 = x_1, \cdots, X_{n-1} = x_{n-1}) \\ & = E\left(\sum_{j=1}^{B_n} E(V_j \mid X_1 = x_1, \cdots, X_{n-1} = x_{n-1}, M_n)\right) \\ & = \lambda e^{-\frac{\lambda}{B_n}} \end{aligned} \tag{14}$$

for $n \in \{1, 2, \cdots\}$. From (10) and (14), we finally have the short-term cognizance rate ρ_n during the nth frame as follows:

$$\rho_n = \frac{\lambda}{A_n + B_n} e^{-\frac{\lambda}{B_n}} \tag{15}$$

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

At the end of the nth frame, the length of the response part of the $(n+1)$st frame is determined to maximize the short-term cognizance rate ρ_{n+1}. Unfortunately, the reader does not know the true value of the parameter λ. Substituting $d_n^{(R)}(x_1, \cdots, x_n)$ for λ, we thus have an approximate short-term cognizance rate during the $(n+1)$st frame

$$\hat{\rho}_{n+1} = \frac{d_n^{(R)}(x_1, \cdots, x_n)}{A + B_{n+1}} e^{-\frac{d_n^{(R)}(x_1, \cdots, x_n)}{B_{n+1}}} \tag{16}$$

where we set the length of the inquiry part $A_n = A$ for all $n \in \{1, 2, \cdots\}$. Let γ be a positive critical point of $\hat{\rho}_{n+1}$ which is a function of the variable B_{n+1}. Then, we have

$$\begin{aligned} \gamma = & \frac{d_n^{(R)}(x_1, \cdots, x_n)}{2} \\ & + \sqrt{\left(\frac{d_n^{(R)}(x_1, \cdots, x_n)}{2}\right)^2 + d_n^{(R)}(x_1, \cdots, x_n) A} \, . \end{aligned} \tag{17}$$

Note that γ is also an extreme point. Thus, we determine the length of the response part of the $(n+1)$st frame as follows:

$$\begin{aligned} & B_{n+1} \\ & = \begin{cases} \lfloor \gamma \rfloor & \text{if } \hat{\rho}_{n+1}(\lceil \gamma \rceil) \le \hat{\rho}_{n+1}(\lfloor \gamma \rfloor) \\ \lceil \gamma \rceil & \text{if } \hat{\rho}_{n+1}(\lceil \gamma \rceil) > \hat{\rho}_{n+1}(\lfloor \gamma \rfloor). \end{cases} \end{aligned} \tag{18}$$

V. Performance Evaluation

In this section, we evaluate the performance of proposed tag cognizance scheme by using a simulation method. For the performance evaluation, we adopt the long-term cognizance rate ξ_j by the end of the jth slot as the performance measure, which is defined as

$$\xi_j = \frac{\sum_{k=1}^{n^*} E(Y_k)}{j} \tag{19}$$

for $j \in \{1, 2, \cdots\}$, where

$$n^* = \max\left\{ n \in \{1, 2, \cdots\} : \sum_{k=1}^{n} (A_k + B_k) \le j \right\}. \tag{20}$$

The simulation environment is as follows:

(1) At the start of each frame, the number of the neighboring tags has the Poisson distribution with mean λ of 10.

(2) The inquiry part of a frame always consists of

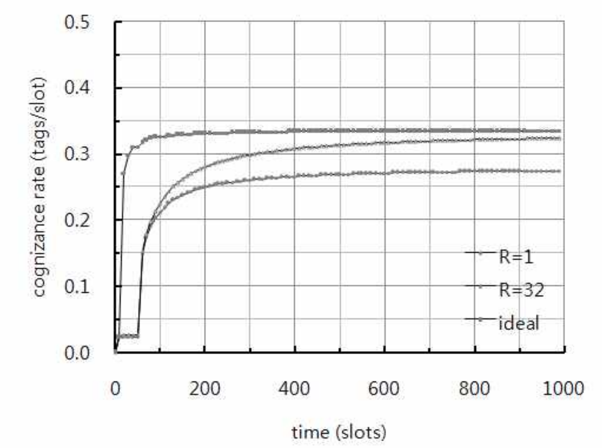

그림 2. 시간의 흐름에 따른 인식율의 수렴
Fig. 2. Convergence of cognizance rate as time goes by.

a single slot, i.e., $A_n = 1$ for all $n \in \{1, 2, \cdots\}$.

(3) The length of the response part of the first frame is fixed to 2, i.e., $B_1 = 2$.

Figure 2 shows the tendency of the long-term cognizance rate as time goes by. In this figure, we compare three rules; 1-retrospective maximum likelihood rule, 32-retrospective maximum likelihood rule and ideal rule (in which the reader exactly knows the true value of the expected number of neighboring tags). We observe that the 32-retrospective rule exhibits a significantly higher cognizance rate than the 1-retrospective rule. Also, we notice that the cognizance rate of the 32-retrospective rule closely approaches to the rate of

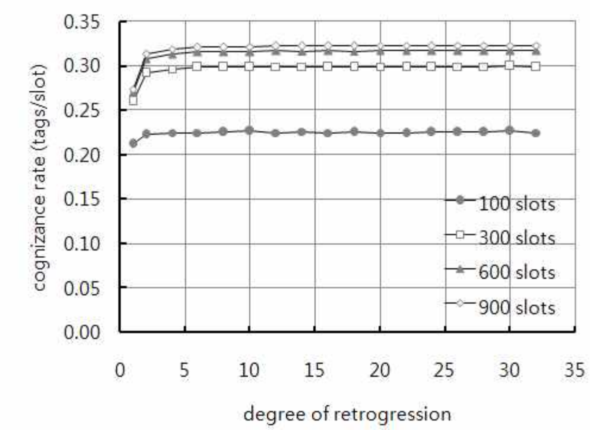

그림 3. 회고 깊이에 따른 장기 인식률
Fig. 3. Long-term cognizance rate with respect to depth of retrospect.

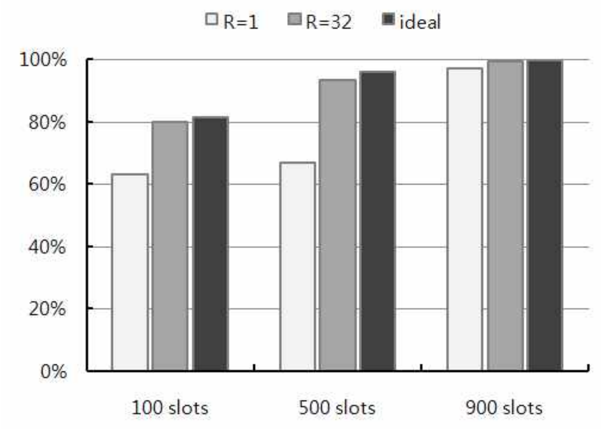

그림 4. 상계에 대한 장기 인식률의 비율
Fig. 4. Ratio of long-term cognizance rate against upper bound.

the ideal rule.

Figure 3 shows the long-term cognizance rate with respect to the depth of retrospect. In this figure, we observe that the long-term cognizance rate becomes higher as the depth of retrospect gets greater at any time.

When the parameter λ is equal to 10, the optimal length of the response part, which maximizes the short-term cognizance rate, is 11. The repetition of such a time structure (inquiry part of 1 slot and response part of 11 slots) produces an upper bound of the long-term cognizance rate, which is calculated to be 0.335742. Figure 4 shows the normalized long-term cognizance rate with respect to the upper bound of 0.335742. In this figure, we observe that a great depth of retrospect is able to invoke an almost ideal performance of long-term cognizance rate in a relatively short time.

Ⅵ. Conclusions

In this paper, we considered an RFID network configured as a star in which tags stationarily move into and out of the vicinity of the reader. To cognize the neighboring tags in the RFID network, we presented a scheme based on dynamic framed and slotted ALOHA which determines the number of slots provided in a frame as to maximize the short-term cognizance rate during the frame. Such an optimization requires the information about the number of neighboring tags. However, the reader hardly knows it. Thus, we proposed a rule for estimating the expected number of neighboring tags, identified as R-retrospective maximum likelihood rule, where the observations attained in the R previous frames are used in maximizing the likelihood of expected number of tags. Simulations result showed that a slight increase in depth of retrospect is able to significantly improve the cognizance performance. Also, observed was that a great depth of retrospect can invoke almost ideal long-term cognizance rate in a relatively short time.

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