

논문 2012-49TC-1-7

# 게임으로 만들어진 슬롯화된 ALOHA를 위한 Bayes 풍의 예측

( Bayesian Prediction for Game-structured Slotted ALOHA )

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**요약**

게임 이론적 시각으로  $p$ -persistence 슬롯화된 ALOHA를 비협력 게임으로 구성하고, 이 게임에서 Nash equilibrium을 구해 찾아 페킷 전달을 시도할 확률 값을 마련한다. Nash equilibrium의 수학적 표현에는 반드시 활성 변방국의 수가 포함되지만, 많은 실제 응용에서 이러한 수를 거의 알 수가 없다. 따라서 본 논문에서는 페킷의 전달을 시도할 지 결정하기에 앞서 활성 변방국의 수를 예측하는 Bayes 풍의 방식을 제안한다. 제안하는 Bayes 풍의 방식은 변방국이 스스로 자연스럽게 구할 수 있는 최소 정보만을 필요로 하지만 상당량의 정보에 의존하는 방식에 비해 경쟁력 있는 예측 성능을 보여 준다.

**Abstract**

With a game-theoretic view,  $p$ -persistence slotted ALOHA is structured as a non-cooperative game, in which a Nash equilibrium is sought to provide a value for the probability of attempting to deliver a packet. An expression of Nash equilibrium necessarily includes the number of active outer stations, which is hardly available in many practical applications. In this paper, we thus propose a Bayesian scheme of predicting the number of active outer stations prior to deciding whether to attempt to deliver a packet or not. Despite only requiring the minimal information that an outer station is genetically able to acquire by itself, the Bayesian scheme demonstrates the competitive predicting performance against a method which depends on heavy information.

**Keywords:** p-persistence slotted ALOHA, game theory, prediction, Bayesian

**I. Introduction**

Slotted ALOHA is a famous scheme of random multiple access<sup>[1]</sup>. Slotted ALOHA and its variants are widely used in many wireless networks, e.g., cellular networks, local and metropolitan area networks and sensor networks. In a slotted ALOHA, a phenomenon called collision occurs inevitably so that a scheme is required for arbitrating a collision. A  $p$ -persistence scheme is one of the collision arbitration schemes which lets an active station

attempt to send a packet with probability  $p$ . Recently, such a classical slotted ALOHA was interpreted with a game-theoretic view and a non-cooperative game was constructed<sup>[2-3]</sup>. In the game, a Nash equilibrium was then found to provide a value for the attempt probability  $p$ . Since active stations are the players of the game, the information about the number of active stations is necessary to find a Nash equilibrium. Unfortunately, such information is hardly available in many practical applications. A way of overcoming such a difficulty is to predict the number of active stations ahead of attempting to deliver a packet. A precise prediction usually needs a plenty of information, e.g., traffic load matrix over the network and network-wise perception of the detailed results

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※ The present research was supported by the research fund of Dankook University in 2010.  
접수일자: 2011년12월31일, 수정완료일: 2012년1월17일

of packet delivery attempts. However, such information is not often available in the network governed by game-structured ALOHA, where a station is only acquainted with the results of its own delivery attempts.

In this paper, we thus propose a Bayesian scheme, which, not knowing the traffic load matrix and the result of other's delivery attempt, predicts the number of active stations. The Bayesian scheme distinctively uses the prior information about the number of active stations. Then, the scheme finds a Bayes action which minimizes the posterior expected loss<sup>[4~5]</sup>. The Bayes action yields an approximate Nash equilibrium hence a value for the attempt probability  $p$ .

Section II describes a model for  $p$ -persistence slotted ALOHA system. In section III, a non-cooperative game is constructed and a Nash equilibrium is presented in a closed form. In section IV, a Bayesian scheme is proposed for predicting the number of active stations. Section IV is devoted to the performance evaluation of the proposed Bayesian scheme.

## II. Model

We consider a wireless network in which a center station is surrounded by many outer stations. Time is slotted in the wireless channel between center and outer stations. Sharing the wireless channel, the outer stations send data segments called packets to the center station. At each outer station, a packet arrives with probability  $\lambda \in [0,1]$  while no packet arrives with probability  $1 - \lambda$  in a slot independently. Also, each outer station is then equipped with a buffer which can hold at most a single packet at any time. Thus, a packet is rejected and lost forever if it arrives at an outer station with full buffer. On the other hand, a packet arriving at an empty buffer is admitted and stored at the buffer.

The packet delivery of outer stations is supported by a random multiple access scheme named slotted

ALOHA. At the start of a slot, an outer station which is active, i.e., having a packet to send, decides whether it attempts to deliver the packet or not with a certain probability according to  $p$ -persistence scheme. Once the outer station decides to attempt, it sends a packet during the slot and is notified about the result of the attempt (either success or failure) within the slot. Otherwise the outer station waits until the next slot begins.

## III. Game

Game theory has been employed to determine the value of the attempt probability in the slotted ALOHA using  $p$ -persistence scheme. In this section, we construct a non-cooperative game and find a Nash equilibrium to determine the value of the attempt probability.

Suppose that there are  $L + 1$  outer stations, named  $1, \dots, L + 1$ , in the wireless network. Let us focus on the behavior of outer station 1 hereafter. Suppose that outer station 1 is active at the start of the  $k$ th slot for  $k \in \mathbb{N}$ . Assume that  $M_k$  outer stations besides outer station 1 are active. Let  $\pi_1, \dots, \pi_{M_k+1}$  denote the active outer stations, where  $\pi_1 = 1$ . These  $M_k + 1$  active outer stations are the players participating in the game during the  $k$ th slot. Then, each player has only two pure strategies; attempting to deliver a packet and not attempting, denoted by  $\sigma_1$  and  $\sigma_2$ , respectively. Let  $S_j$  denote the strategy of player  $\pi_j$  for  $j \in \{1, \dots, M_k + 1\}$ . Let  $U_j(S_1, \dots, S_{M_k+1})$  be the payoff that player  $\pi_j$  receives when player  $\pi_i$  uses strategy  $S_i$  for  $i \in \{1, \dots, M_k + 1\}$ . Then, we set

$$U_j(S_1, \dots, S_{M_k+1}) = \begin{cases} \alpha & \text{if } S_j = \sigma_1 \text{ a.s. and } S_i = \sigma_2 \text{ a.s.} \\ & \text{for all } i \neq j \\ \beta & \text{if } S_j = \sigma_1 \text{ a.s. and } S_i = \sigma_1 \text{ a.s.} \\ & \text{for some } i \neq j \\ \gamma & \text{if } S_j = \sigma_2 \text{ a.s.} \end{cases} \quad (1)$$

for each  $j \in \{1, \dots, M_k + 1\}$ . Note that  $\alpha$  is the payoff that player  $\pi_j$  receives when it succeeds in delivery attempt. The payoff  $\alpha$  reflects a mixture of the reward for delivering a packet and the penalty for consuming energy. On the other hand,  $\beta$  is the payoff that player  $\pi_j$  receives when it fails in delivery attempt. The payoff  $\beta$  represents both of the penalty for packet delay (or packet loss) incurred by not delivering a packet and the penalty for consuming energy. If player  $\pi_j$  does not attempt to deliver, it receives the payoff  $\gamma$ . The payoff  $\gamma$  stands for the reward for saving energy combined with the penalty for not delivering a packet. Apparently, it is reasonable to presume that  $\beta < \gamma < \alpha$ .

A mixed strategy  $S_j$  of player  $\pi_j$  is a discrete random variable supporting  $\{\sigma_1, \sigma_2\}$  [6]. A mixed strategy profile  $(S_1, \dots, S_{L+1})$  is a family of mixed strategies collected from every player. Among the set of all mixed strategy profiles, a Nash equilibrium  $(S_1^*, \dots, S_{L+1}^*)$  is defined to be a special profile such that

$$\begin{aligned} & E(U(S_1^*, \dots, S_{j-1}^*, S_j^*, S_{j+1}^*, \dots, S_{L+1}^*)) \\ & \leq E(U(S_1^*, \dots, S_{j-1}^*, S_j, S_{j+1}^*, \dots, S_{L+1}^*)) \end{aligned} \quad (2)$$

for all  $S_j$  and  $j \in \{1, \dots, L+1\}$ . In other words, a Nash equilibrium is a strategy profile such that a player can not increase its expected payoff by using a strategy other than the strategy in the profile if all other players adopt the strategies in the profile. Under the assumption that the true value of  $M_k$  is known, a Nash equilibrium was presented in [3] as follows:

**Theorem 1.** Let  $S_j^*$  be a mixed strategy of player  $\pi_j$  such that

$$P(S_j^* = \sigma_1) = 1 - \left(\frac{\gamma - \beta}{\alpha - \beta}\right)^{\frac{1}{M_k}} \quad (3)$$

for  $j \in \{1, \dots, M_k + 1\}$ . Then, the mixed strategy profile  $(S_1^*, \dots, S_{M_k+1}^*)$  is a Nash equilibrium.

Thus, outer station 1 with rational mind attempts

to deliver a packet with probability  $P(S_1^* = \sigma_1)$  at the start of the  $k$ th slot.

#### IV. Prediction

Apparently, the attempt probability provided by a Nash equilibrium depends on the number of active outer stations. Unfortunately, an outer station, in practice, hardly knows how many outer stations are active. As a result, the expression of the attempt probability in (3) may be obsolete unless the information about the number of active outer stations is available. In this section, we thus propose a Bayesian scheme of predicting the number of active outer stations prior to deciding whether to attempt to deliver a packet or not.

To predict the number of active outer stations, we formulate a decision problem, which is a triple  $(\mathbf{M}, \mathbf{A}, L)$ . Recall that  $M_k$  denote the number of other active outer stations. Then, the first component of the problem, which is called the parameter space,  $\mathbf{M}$  is the support of  $M_k$ . Thus,  $\mathbf{M} = \{0, \dots, L\}$ . The second component  $\mathbf{A}$  is the action space which is a collection of the estimates of the parameter  $M_k$ . Including non-integer values, we set  $\mathbf{A} = [0, L]$ . The last component is the loss function  $L: \mathbf{M} \times \mathbf{A} \rightarrow \mathbb{R}$  such that  $L(m, a)$  represents the loss incurred by action  $a$  when  $M_k = m$ . We assume a squared error loss, i.e.,  $L(m, a) = (m - a)^2$ .

For  $k \in \mathbb{N}$ , let  $X_k$  denote the number of packets residing in the buffer of outer station 1 at the start of the  $k$ th slot. Note that  $X_k \in \{0, 1\}$  since every outer station is only equipped with a single buffer. Let  $R_k$  indicate whether outer station 1 is acknowledged by the center station or not as follows: Suppose that outer station 1 is active and attempts to deliver a packet in the  $k$ th slot. If outer station 1 is acknowledged, (i.e., succeeds in delivery attempt without collision),  $R_k$  is set to 1. Otherwise,  $R_k$  is set to -1. If outer station 1 does not attempt to deliver, it is never acknowledged and  $R_k$  is set to 0.

Let  $p_k$  denote the attempt probability adopted by outer station 1 at the start of the  $k$ th slot. Assume that outer station 1 believes that every other active outer station employs the same attempt probability as itself. Then, the conditional mass for  $M_k$ , which is also called the likelihood of  $M_k$ , is calculated to be

$$\begin{aligned} f_1(1 \mid m) &= P(R_k = 1 \mid M_k = m, X_k = 1) \\ &= p_k(1 - p_k)^m \\ f_1(0 \mid m) &= P(R_k = 0 \mid M_k = m, X_k = 1) \\ &= 1 - p_k \end{aligned}$$

$$\begin{aligned} f_1(-1 \mid m) &= P(R_k = -1 \mid M_k = m, X_k = 1) \\ &= p_k[1 - (1 - p_k)^m] \end{aligned}$$

$$f_0(0 \mid m) = P(R_k = 0 \mid M_k = m, X_k = 0) = 1$$

$$\text{for } m \in \mathbf{M}. \quad (4)$$

With the help of the observables  $R_k$  and  $X_k$ , we may be able to take a precise action. Let  $h_x(m \mid r)$  denote the posterior mass for  $M_k$  when  $R_k = r \in \{-1, 0, 1\}$  and  $X_k = x \in \{0, 1\}$  are observed. Then,

$$h_x(m \mid r) = \frac{f_x(r \mid m)g_x(m)}{\sum_{l=0}^L f_x(r \mid l)g_x(l)} \quad (5)$$

for  $m \in \mathbf{M}$ , where  $g_x$  is the prior mass for  $M_k$  when  $X_k = x$ . For example, suppose a binomial prior with parameters  $L$  and  $\delta_k$ , i.e.,

$$g_x(m) = \binom{L}{m} \delta_k^m (1 - \delta_k)^{L-m} \quad (6)$$

for  $m \in \mathbf{M}$  regardless of  $x \in \{0, 1\}$ . Then, we have

$$\begin{aligned} h_1(m \mid 1) &= \frac{\binom{L}{m}(\delta_k - \delta_k p_k)^m (1 - \delta_k)^{L-m}}{(1 - \delta_k p_k)^L} \\ h_1(m \mid 0) &= \binom{L}{m} \delta_k^m (1 - \delta_k)^{L-m} \\ h_1(m \mid -1) &= \frac{\binom{L}{m}(1 - \delta_k)^m (1 - \delta_k)^{L-m}}{1 - (1 - \delta_k p_k)^L} \end{aligned} \quad (56)$$

$$\begin{aligned} &- \frac{\binom{L}{m}(\delta_k - \delta_k p_k)^m (1 - \delta_k)^{L-m}}{1 - (1 - \delta_k p_k)^L} \\ h_0(m \mid 0) &= \binom{L}{m} \delta_k^m (1 - \delta_k)^{L-m} \end{aligned} \quad (7)$$

for  $m \in \mathbf{M}$ . Now, we find a Bayes action which minimizes the posterior expected loss  $E_x(L(M_k, a) \mid R_k = r)$ . Let  $a^*$  denote a Bayes action. Then,  $a^*$  is the posterior mean  $E_x(M_k \mid R_k = r)$ . For the binomial prior,  $a^*$  is obtained to be

$$a^* = \begin{cases} \frac{L\delta_k(1 - p_k)}{1 - \delta_k p_k} & \text{if } R_k = 1, X_k = 1 \\ L\delta_k & \text{if } R_k = 0, X_k = 1 \\ \frac{L\delta_k[1 - (1 - p_k)(1 - \delta_k p_k)^{L-1}]}{1 - (1 - \delta_k p_k)^L} & \text{if } R_k = -1, X_k = 1 \\ L\delta_k & \text{if } R_k = 0, X_k = 0 \end{cases} \quad (8)$$

which is used to estimate  $M_k$  and is also used to predict  $M_{k+1}$ .

As slots go by, an outer station experiences more observables, which may bring about more precise prior distribution. In this paper, we update the prior mean in a slot by the posterior mean in the previous slot. In the binomial prior, for example, we set

$$\delta_{k+1} = \frac{E_x(M_k \mid R_k = r)}{L} \quad (9)$$

for  $k \in \mathbb{N}$ , where the posterior mean  $E_x(M_k \mid R_k = r)$  is given in (8).

## V. Performance

In this section, we evaluate the proposed Bayesian scheme. For the performance comparison, we consider a method presented by Rivest for estimating the number of active stations in a slotted ALOHA network<sup>[7]</sup>. Note that the method requires an outer

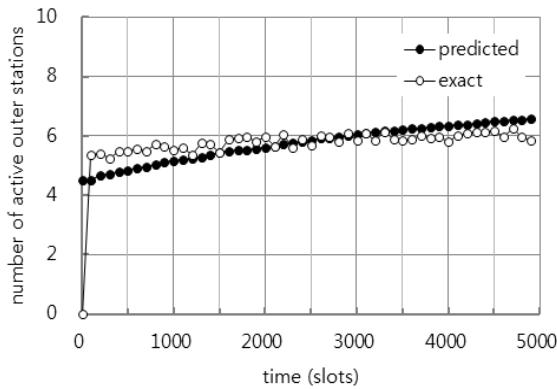


그림 1. 시간의 흐름에 따른 활성 변방국의 예측된 수와 실제 수의 변화 (제안하는 Bayes 풍의 방식)  
Fig. 1. Change of predicted and exact numbers of outer stations with respect to time. (proposed Bayesian scheme).

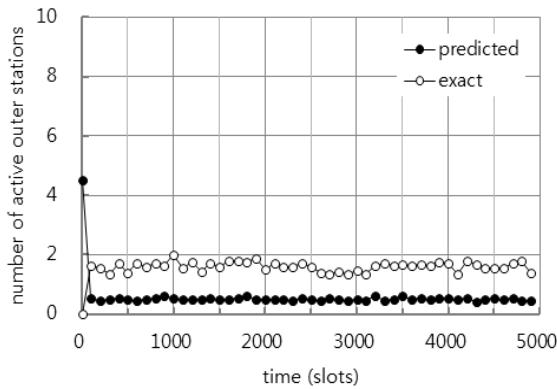


그림 2. 시간의 흐름에 따른 활성 변방국의 예측된 수와 실제 수의 변화 (Rivest의 방식)  
Fig. 2. Change of predicted and exact numbers of outer stations with respect to time. (Rivest method).

station to know the traffic load matrix over the network and the detailed result of delivery attempt success in attempt, no attempt and collision) in every slot. However, the proposed Bayesian scheme needs none of them.

As slots go by, figures 1 and 2 show the numbers of other active outer stations (which are observed by outer station 1) predicted by the Bayesian scheme and Rivest method, respectively. In these figures, the network is assumed to consist of 10 outer stations, which are symmetrically loaded with 0.03 packets/slot in a Bernoulli fashion. The payoffs  $\alpha$ ,  $\beta$  and  $\gamma$  are also set to be 1, -1 and 0.8,

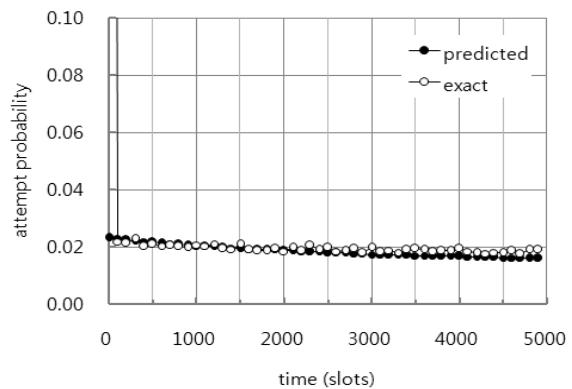


그림 3. 시간의 흐름에 따른 전달 시도 확률의 변화 (제안하는 Bayes 풍의 방식)  
Fig. 3. Change of delivery attempt probability with respect to time. (proposed Bayesian scheme).

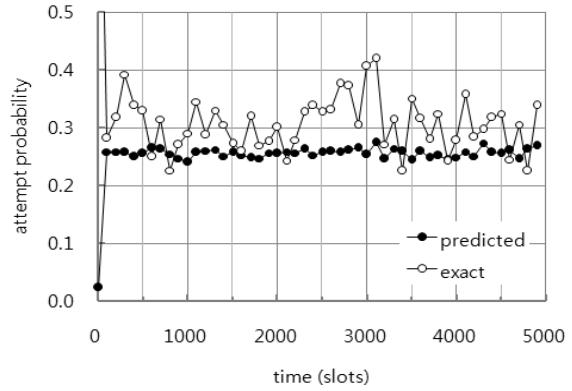


그림 4. 시간의 흐름에 따른 전달 시도 확률의 변화 (Rivest의 방식)  
Fig. 4. Change of delivery attempt probability with respect to time. (Rivest method)

respectively. From these figures, we observe that the Bayesian scheme tends to predict the number of active outer stations more precisely than Rivest method.

Figures 3 and 4 illustrate the values of the attempt probability yielded by the Bayesian scheme and Rivest method, respectively. In these figures, the same environment is formed as in figures 1 and 2. To the attempt probability produced by the exact number of active outer stations, the attempt probability yielded by the Bayesian scheme seems to be closer than the one made by Rivest scheme.

Figure 5 shows the normalized difference in attempt probability, which is defined as the ratio of the absolute difference in exact and approximate

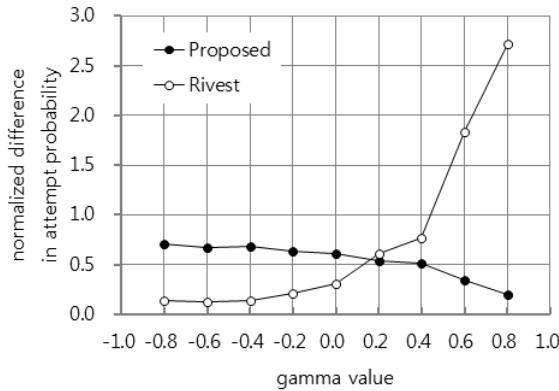


그림 5. Payoff  $\gamma$ 의 변화에 따른 전달 시도 확률의 정 규화된 차이

Fig. 5. Normalized difference in attempt probability with respect to payoff  $\gamma$ .

attempt probabilities against exact attempt probability. In this figure, the same environment as in figures 1 and 2 is basically assumed and the value of attempt probability is sampled in the 5000th slot. For a low value of  $\gamma$ , Rivest method seems to generate a closer attempt probability to the exact one compared with the Bayesian scheme. However, the precision of the Bayesian scheme is significantly improved as the value of  $\gamma$  is increased. Note that  $\gamma$  represents the importance of energy saving so that a high value of  $\gamma$  makes a outer station hesitate to attempt to deliver a packet.

## VI. Conclusion

With a game-theoretic view, p-persistence slotted ALOHA was structured as a non-cooperative game, where a Nash equilibrium was found to provide a value for the attempt probability  $p$ . The knowledge on the number of active outer stations is necessary to express the Nash equilibrium. Unfortunately, such information is hardly available in many practical applications. In this paper, we thus proposed a Bayesian scheme of predicting the number of active outer stations ahead of deciding whether to attempt to deliver a packet or not. The Bayesian scheme is characterized by an outer station's believing in a prior distribution for the number of active outer

stations and only observing the result of its own delivery attempt. Despite only requiring the minimal information that an outer station is genetically able to acquire by itself, the Bayesian scheme demonstrated the competitive predicting performance against Rivest method which depends on heavy information; the Bayesian scheme exhibited a significantly smaller normalized difference in attempt probability when the value of payoff  $\gamma$  is relatively high.

## References

- [1] R. Rom and S. Sidi, Multiple Access Protocols – Performance and Analysis. Springer-Verlag, 1990.
- [2] A. MacKenzie and S. Wicker, "Selfish Users in ALOHA: A Game-theoretic Approach," Proceedings of IEEE VTC 2001 Fall, pp. 1154–1357, 2001.
- [3] J. Park, J. Ha, H. Seo, J. Kim, and C. Choi, "Stability of Game-theoretic Energy-aware MAC Scheme for Wireless Sensor Networks," Proceedings of IEEE SUTC 2010, pp. 384–389, 2010.
- [4] T. Ferguson, Mathematical Statistics – A Decision Theoretic Approach. Academic Press, 1967.
- [5] J. Berger, Statistical Decision theory and Bayesian Analysis. Springer-Verlag, 1985.
- [6] E. Barron, Game Theory – An Introduction. John Wiley and Sons, 2008.
- [7] D. Bersekas and R. Gallager, Data Networks. Prentice Hall, 1987.

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