LETTER

An Adaptive RFID Anti-Collision Algorithm Based on Dynamic Framed ALOHA

ChangWoo LEE[†a)], **Hyeonwoo CHO**[†b)], ***Nonmembers, and*** **Sang Woo KIM**[††c)], ***Member***

SUMMARY The collision of ID signals from a large number of co-located passive RFID tags is a serious problem; to realize a practical RFID systems we need an effective anti-collision algorithm. This letter presents an adaptive algorithm to minimize the total time slots and the number of rounds required for identifying the tags within the RFID reader's interrogation zone. The proposed algorithm is based on the framed ALOHA protocol, and the frame size is adaptively updated each round. Simulation results show that our proposed algorithm is more efficient than the conventional algorithms based on the framed ALOHA.

key words: *RFID, anti-collision, framed-ALOHA*

1. Introduction

Radio frequency identification (RFID) technology is becoming an important alternative to the traditional bar-code system [1]. The RFID system consisting of an RFID reader and tags can recognize tagged objects by using wireless communication [2]. In case of passive RFID system, when there are many passive tags in an RFID reader's interrogation zone, the RFID reader can not read all the tags at a time because of collisions. Therefore, an anti-collision algorithm is required for identifying each tag as fast and as efficiently as possible.

The anti-collision algorithms are classified into deterministic and stochastic methods [3]. The deterministic method is tree-based whereas the stochastic method is ALOHA-like anti-collision protocol. In this letter, we will focus on the ALOHA-like protocol, especially on the dynamic framed ALOHA protocol.

An RFID reader using the dynamic framed ALOHA protocol initially sends RF signals to tags for synchronization and declaration of the frame size (the number of time slots) which is determined adaptively [3]. The tags, then, randomly select a time slot and transmit their ID at the slot time. This cycle is called a round. Since the tags can not arbitrate each other, more than two tags may take the same time slot, and then a collision would occur at the time slot. If some collisions are detected by an RFID reader, the reader repeatedly attempts retransmission.

In case of a dynamic framed ALOHA protocol, the condition for maximum throughput demands that the frame size be equal to the number of the mobile nodes [4]. Therefore, if the RFID reader sets the frame size to the number of tags in its interrogation zone, the maximum throughput can be achieved. Because an RFID reader does not know the number of tags, a process of estimating the number of tags is needed for achieving the best performance.

In a recently proposed dynamic framed ALOHA anti-collision algorithm which uses the method of estimating the number of tags to determine a frame size, two methods have been introduced [3]. One is to estimate the number of tags from the number of empty slots based on the occupancy theorem [5]. The other method is to estimate the number of tags from the number of empty and success slots based on binary distribution. The first method, despite its good performance, suffers from a high numerical complexity in calculating the maximum likelihood of a probability of occupancy problems. Although a pre-calculated reference table to minimize the numerical complexity is recommended by the authors [3], it is not sufficient to yield the optimal frame size for all the exceptional cases. The second method is easy to compute, but an upper bound value which is not adaptively determined is used in some special cases. Therefore, the performance of the second method depends on the number of tags in the interrogation zone and on the user defined upper bound value.

In this letter, we introduce an algorithm that has the ability to adaptively determine all the special cases and also has reasonable computational complexity. To achieve this, the data obtained from the result of each round are split into three cases, and different equations are used for each case to estimate the number of tags. Simulation results demonstrate the performance of the proposed algorithm by comparing to the second methods of [3] (hereinafter referred as "the Chen's method" throughout the letter).

In this letter, the following notations and definitions are adopted:

$E(\cdot)$: Expectation operation
$W(\cdot)$: Lambert W function
$W_0(\cdot)$: Principal branch of Lambert W function
$W_{-1}(\cdot)$: Non-principal branch of Lambert W function
$\ln(\cdot)$: Natural logarithm function
e: The base of natural logarithm
N : The frame size in the present round
n : The actual number of the tags in the present round

Manuscript received June 14, 2007.
Manuscript revised September 4, 2007.

[†]The authors are with the Ph.D. candidate of Dept. of Electronic and Electric Engineering, POSTECH, Hyoja-dong, Pohang, Korea.
[††]The corresponding author is with the Faculty of Dept. of Electronic and Electric Engineering, POSTECH, Hyoja-dong, Pohang, Korea.
a) E-mail: caprix@postech.edu
b) E-mail: lighto@postech.edu
c) E-mail: swkim@postech.edu

DOI: 10.1093/ietcom/e91–b.2.641

r : The estimated number of the tags in the present round
I : The number of idle slots
S : The number of success slots
C : The number of collision slots
where idle slot means that there is no tag in a slot, success slot means that there is only one tag in a slot, and collision slot means that there are more than two tags in a slot. The equality $N = I + S + C$ must be satisfied for all the rounds.

2. The Proposed Algorithm

We propose a new algorithm that estimates the number of tags based on the dynamic framed ALOHA anti-collision protocol scheme of [3]. At the end of each round, an RFID reader can acquire some data which are I, S and C by counting the number of idle, success, collision slots, respectively. Then the RFID reader can estimate r by using I, S, C and the known value N. After the estimation, the RFID reader sets the frame size for the next round to the number of unread tags which is equal to $r - S$ for achieving the maximum throughput. This dynamic framed ALOHA anti-collision protocol scheme runs until no collisions are detected. In Table 1, we present the pseudo code of our proposed estimation algorithm.

3. Analysis of the Proposed Algorithm

Our algorithm is based on two Eqs. (1) and (2) like the Chen's method.

Table 1 The pseudo code of the proposed algorithm.

```
arguments I, C, S, N
β greater than 0 and less than 1;
if(I != 0) //if idle slots exist (That is N!=C + S)
  estimatedTags = ln(1 − (C + S)/N)/ ln(1 − 1/N);
elseif (I == 0)//I is equal to 0(No idle state)
  if (S != 0)//No idle. Both S and C are not zero.
    A = 1 − 1/N;
    B = S ∗ A;
    //if there exist any solutions in the Lambert W function
    if -1/e ≤ B ln(A) ≤ 0
      estimatedTags = W_{−1}(B ∗ ln(A))/ ln(A);
    // No real solution in lambert W function
    elseif B ∗ ln(A) < −1/e
      α = ln(β/N)/(C ∗ ln(1 − 1/N));
      estimatedTags = α ∗ C;
    end
  elseif (S == 0) // No idle and No success. only collision
    if(N == 1) // for only one slot
      α = 2;
    else //more than 2 slots
      α = ln(β/N)/(C ∗ ln(1 − 1/N));
    end
    estimatedTags = α ∗ C;
  end
end
unreadTags = estimatedTags - S;
frameSizeForNextRound = unreadTags;
```

$$E(I) = N\left(1 - \frac{1}{N}\right)^n, \tag{1}$$

$$E(S) = n\left(1 - \frac{1}{N}\right)^{n-1} \tag{2}$$

where n is unknown.
From the assumption that $E(I)$ is equal to I and $E(S)$ is equal to S, (1) and (2) can be expressed as (3) and (4), respectively,

$$I \approx N\left(1 - \frac{1}{N}\right)^n, \tag{3}$$

$$S \approx n\left(1 - \frac{1}{N}\right)^{n-1}. \tag{4}$$

If we use an estimated value r instead of true n,

$$I = N\left(1 - \frac{1}{N}\right)^r, \tag{5}$$

$$S = r\left(1 - \frac{1}{N}\right)^{r-1} \tag{6}$$

which may contain approximation errors.
In the Chen's method, the number of estimated tags is derived from the simultaneous equations of (5) and (6), where the equations are over-determined because the two equations have only one unknown variable r. This makes the Chen's method to have three special cases [3]. Therefore, to treat the special cases more adaptively, we separately solve (5) and (6) for r. Equation (5) is easily solved for r through simple arithmetic operations. On the other hand, Eq. (6) can not be solved analytically for r. Therefore we adopt the Lambert W function [6] to solve (6). In this section, we will split the pseudo code into some subparts and explain them, respectively.

1) $I! = 0$: This case means that there are more than one idle slots. In this case, C never becomes zero because $C = 0$ means that all tags have transmitted their ID at the previous round.

For deriving a suitable equation for this case, we adopt Eq. (5) and substitute $N - (C + S)$ for I of (5),

$$N - (C + S) = N\left(1 - \frac{1}{N}\right)^r, \tag{7}$$

dividing both sides by N and taking natural logarithm,

$$r = \frac{\ln\left(1 - \dfrac{C + S}{N}\right)}{\ln\left(1 - \dfrac{1}{N}\right)}. \tag{8}$$

By using (8), we can easily estimate r. However, if N is equal to $C + S$ or 1, (8) can not work. Both $N == C + S$ and $N == 1$ mean that there are no idle slots. To develop new equations available for $I == 0$, we will divide this case into two different subcases. One is $I == 0$, $S! = 0$ and the other is $I == 0$, $S == 0$.

2) $I == 0, S! = 0$: This case means that there are no idle slots, and S is not zero. To handle this case, in [3], the following algorithm is used. If $C > S$, r was set to the upper bound value and if $C < S$, r was set to $2 \times C$, which is the lower bound of the number of tags. It is somewhat reasonable but not an adaptive method. Therefore, we propose an adaptive approach as follows.

From Eq. (6), we can simplify as

$$B = rA^r, \tag{9}$$

where the parameters are defined as follows,

$$A = \left(1 - \frac{1}{N}\right) \text{ and } B = S\left(1 - \frac{1}{N}\right) = SA. \tag{10}$$

By applying Lambert W function, we can solve (9) with respect to r,

$$r = \frac{W(B\ln(A))}{\ln(A)}, \tag{11}$$

where $W(\cdot)$ means Lambert W function.

At this point, the Lambert W function that is formulated as

$$W(z)\exp^{W(z)} = z \tag{12}$$

must be considered.

According to the property of Lambert W function, if $z \geq 0$, only one real value exists for $W(z)$. If $-1/e \leq z < 0$, two real values, which are *principal branch* value and *non-principal branch* value, exist for $W(z)$. If $z < -1/e$, no real value exists for $W(z)$ [6]. Based on these properties, we consider our anti-collision problem. The $B\ln(A)$ at (11) is always satisfied with $B\ln(A) < 0$ because of $0 < A < 1$ and $B > 0$. Hence, using (11), we can compute two different estimated numbers of tags for $-1/e \leq B\ln(A) \leq 0$, and no real estimated number of tags for $B\ln(A) \leq -1/e$.

Therefore, when $-1/e \leq B\ln(A) \leq 0$ is satisfied, we should consider whether the value is a suitable solution for the estimated number of tags. Since the lower bound of the estimated number of tags is $2 \times C$, the r that is greater than $2 \times C$ is chosen. According to this consideration, we choose r that is derived from *non-principal branch*. Because if we compute r through *principal branch*, the r would be always less than $2 \times C$. Thus the estimated number of tags is calculated as

$$r = \frac{W_{-1}(B\ln(A))}{\ln(A)}. \tag{13}$$

When $B\ln(A) \leq -1/e$ is satisfied, (11) has no real solution. Therefore, we can not use Lambert W function. Thus we have to develop another equation. To do this, we assume that the average value of I is less than 1 because the measured I is zero in this case. If the average value of I is more than 1, the probability of the measured I being equal to 1 is increased, and the estimation errors are certainly increased. Therefore, we set the average of I to β, which is less than 1, and use $\alpha \times C$ for r instead of $2 \times C$, which is used in [3]. Using (1) again,

$$\beta = N\left(1 - \frac{1}{N}\right)^{\alpha * C}, \tag{14}$$

$$\left(1 - \frac{1}{N}\right)^{\alpha * C} = \frac{\beta}{N}, \tag{15}$$

$$\alpha = \frac{\ln\left(\frac{\beta}{N}\right)}{C\ln\left(1 - \frac{1}{N}\right)}, \tag{16}$$

where $0 < \beta < 1$ and β is a user defined value. From the equations, we calculate α and estimate r as $\alpha * C$. Therefore the estimated number of unread tags is $(\alpha * C) - S$.

3) $I == 0, S == 0, N == C$: This condition means all tags have collided. In other words, there are no idle slots and success slots. In [3], an upper bound value of the number of tags is used for r. As opposed to [3], we use a variable α and β, which is less than 1, and adaptively calculate r. This method is the same as (16). Using (1) again,

$$\alpha = \frac{\ln\left(\frac{\beta}{N}\right)}{C\ln\left(1 - \frac{1}{N}\right)}, \tag{17}$$

where $0 < \beta < 1$. From (17), we calculate α and estimate r as $\alpha * C$. The estimated number of unread tags is also $\alpha * C$ because S is zero. Finally, the situation where N is equal to 1 is only the condition that (17) is not available. Hence for N, which is equal to 1, we set α to 2 where it is just a lower bound of the number of tags.

4. Simulation Results

Our computer simulations were based on the Monte Carlo method. All the simulation results are obtained by an ensemble averaging over 10000 independent trials. The Lambert W function for the proposed algorithm was conducted by using the one-shot evaluation algorithm which does not require a recurrence relation in [6].

Firstly, we evaluate the performance of the proposed algorithm in terms of total number of time slots which are required to identify all tags. For this simulation, we set the initial frame size to 16, and set β to 0.1. In Fig. 1, the lines referred to as case 1 and case 2 are the results of the Chen's method that requires user-defined bounds. Case 1 is the result obtained when both the lower and the upper bounds are set to $2 * C$, and Case 2 is the result obtained when the lower bound is set to $2 * C$ and the upper bound is set to 256, respectively. These results reveal that the performance of the Chen's method depends on the upper bound whereas the proposed algorithm does not depend on it. Figure 2 shows the detailed difference in the number of total time slots between the Chen's method and the proposed algorithm based

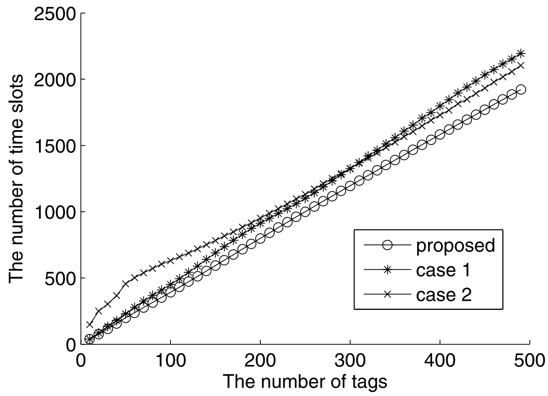

Fig. 1 Comparison of the number of total time slots required in both the proposed algorithm and the Chen's method (case 1 is both 2*collision lower and upper bounds, case 2 is 2*collision lower bound and 256 upper bound).

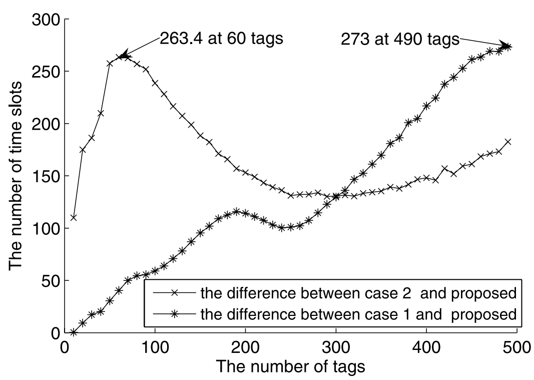

Fig. 2 Comparison of the differences in total time slots between the Chen's method and the proposed algorithm (case 1 is both 2*collision lower and upper bounds, case 2 is 2*collision lower bound and 256 upper bound).

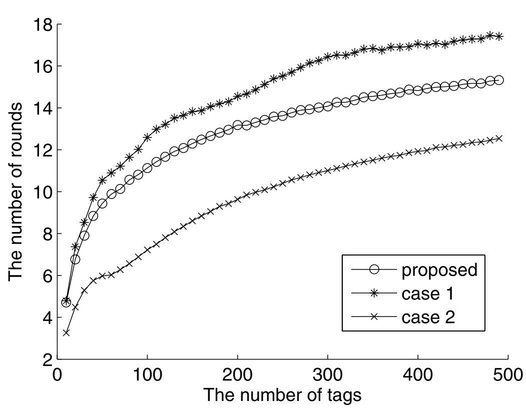

Fig. 3 Comparison of the number of total rounds in the proposed algorithm and the Chen's method (case 1 is both 2*collision lower and upper bounds, case 2 is 2*collision lower bound and 256 upper bound).

on the result of Fig. 1. As can be seen clearly in Fig. 2, the proposed algorithm requires about 263.4 fewer time slots at 60 tags than case 1 of Chen's method, and it requires about 273 fewer time slots at 490 tags than case 2 of Chen's method.

Secondly Fig. 3 shows the total number of rounds. If

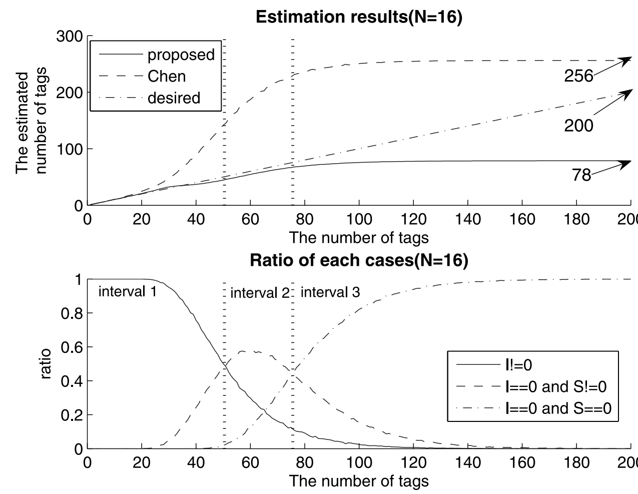

Fig. 4 Estimation performance for the number of tags and the ratio of occurrence for each case when the frame size is assumed to be 16.

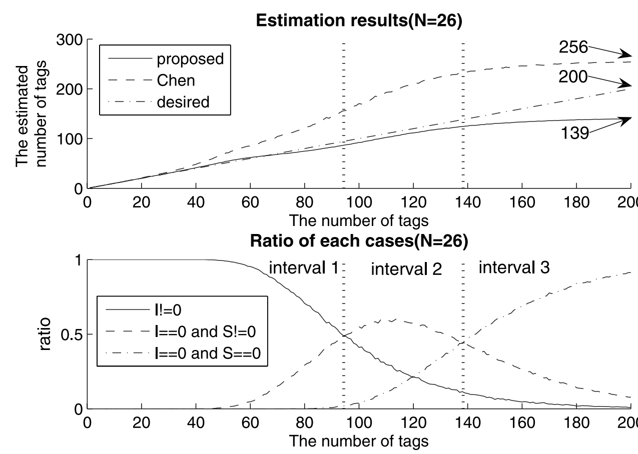

Fig. 5 Estimation performance for the number of tags and the ratio of occurrence for each case when the frame size is assumed to be 26.

the total number of rounds is decreased, the overhead of an RFID reader is decreased [7]. As shown in Fig. 3, the proposed algorithm requires less rounds than the case 1 of the Chen's method, but requires more rounds than the case 2 of the Chen's method. As the case 2 may use a relatively large frame size as 256 at some rounds, the overall number of rounds would be decreased. However the case 2 may spend much more time to read the idle slots.

Finally, we evaluate the estimation performance of the proposed algorithm. An algorithm's ability to estimate the number of tags accurately is very important in achieving the maximum throughput. Figures 4–5 show the estimated number of tags of the proposed algorithm and the Chen's method in which the number of tags varies from 1 to 200 when the frame size is 16 and 26, respectively. In simulation, we set the lower bound to 2*collision and the upper bound to 256 for the Chen's method. Then we assign the tags to the slots randomly. The line named "desired" means the true number of tags which we want to estimate. For more detailed discussion, we also denote the ratio of occurrence of each case of the proposed algorithm. According to the ratio of each case, we divide the horizontal axis into three subintervals named intervals 1, 2 and 3. At interval 3, collisions occur in more than about 95% of slots. Therefore, the equation for the case of $I == 0, S == 0$ is mainly applied for estimation. In this case, the estimation performance of both algorithms is not excellent because there is only information of $N == C$. However, we can see that the proposed algorithm adaptively derives 78 and 139 as an estimated number of tags for the frame size 16 and 26 whereas the Chen's second method derives only 256 regardless of the frame size. At interval 2, the case of $I == 0, S\,! = 0$ is relatively dominant. In this case, the estimation performance of the proposed algorithm is much more accurate than the Chen's method owing to the adaptive treatment using the Lambert W function. At interval 1 where the case of $I! = 0$ is dominant, the estimation performance of both the algorithms is excellent because there are sufficient information for estimating the number of tags. Although the estimation performance of both algorithms is almost the same, the proposed algorithm becomes proportionally more accurate as the number of tags is increased. These findings led us to conclude that the proposed algorithm has better estimation performance in all the cases of $I! = 0$, $I == 0\&S\,! = 0$ and $I == 0\&S == 0$. Thus the proposed algorithm shows a good anti-collision performance in ALOHA demonstrating its ability to deal with the special cases more adaptively.

Compared with the Chen's method, the proposed algorithm may have a relatively higher arithmetic complexity in calculating the logarithm operations and the Lambert W function. Recently, however, the manufacturers of an RFID reader use a DSP processor for high performance protocol implementation. Moreover, fast algorithms to calculate logarithm on a DSP processor [8] and a fast algorithm to calculate the Lambert W function [6] have been developed. Therefore, the proposed algorithm can be implemented practically.

5. Conclusions

This letter presents a fast RFID anti-collision algorithm based on dynamic framed ALOHA. The data obtained from a round are split into three cases based on whether I and S are zero or not. In all cases, we developed adequate equations that can adaptively estimate the number of tags. Simulation results show that the performance of the proposed algorithm is independent of the number of tags and is better than that of the second method of [3]. The computational complexity of the proposed algorithm is also reasonable for practical implementation.

Acknowledgments

This research was supported by Ubiquitous Technology Research Center (UTRC).

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