Capture-Aware Estimation for the Number of RFID Tags with Lower Complexity

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***Abstract*—Capture effect is very common in wireless communication systems. In a passive radio frequency identification (RFID) system, even though multiple tags backscatter their signals to a reader simultaneously, one of the tags will be successfully identified due to the capture effect. In this letter, we propose an algorithm which will optimize the identification efficiency of a dynamic frame length ALOHA RFID protocol under capture effect. The proposed algorithm estimates the number of tags and the probability of capture effect. From these parameters, an optimal frame length can be obtained. The advantage of the algorithm is that it does not need many steps to search an extreme value for the estimation. It thus reduces the computational complexity. Computer simulation results show that the proposed method's identification efficiency is almost identical to existing algorithms, but at lower computational complexity.**

***Index Terms*—RFID, anti-collision, the number of tags, capture effect.**

I. Introduction

Passive radio frequency identification (RFID) can support simultaneous multi-tag identification and hence offers higher identification efficiency than conventional bar code technology. In the passive system, an RFID reader identifies multiple tags on a shared wireless channel. Therefore, when more than two tags backscatter their signals to the reader simultaneously, collision may happen and will disturb the identification. The multi-tag identification is actually a multi-access communication system. Generally, anti-collision algorithms [1] for multi-access systems can be applied to the RFID tag collision problem. Under capture effect, however, more than two tag signals might not necessarily lead to collision. Capture effect is very common in a wireless communication system. A tag that is near to a reader will backscatter a much stronger signal than one that is far away. The near tag will be detected and the far tag will be hidden [2]. In recent years, how to optimally solve the collision under capture effect has attracted much attention [2-4].

Optimal Q algorithm [3] is an ALOHA-based anti-collision algorithm under capture effect. In order not to miss the hidden tags, the algorithm lets the hidden tags enter the next frame to be identified again. However, optimal Q algorithm adopts the idea of a dynamic frame length ALOHA protocol [5]. That is, each frames length is set to the number of unidentified tags. When capture effect happens, the setting could not guarantee optimal efficiency. General binary tree (GBT) algorithm [2] is a binary tree-based anti-collision algorithm [6] under capture effect. The algorithm divides an identification cycle into several binary trees. Like Optimal Q algorithm, GBTs hidden tags will also enter the next tree. Thus the hidden tags will not be missed. However, GBT does not yet give an optimal relationship between the number of slots and the number of tags. The identification efficiency of GBT does not achieve an optimal value, either. Capture-aware backlog estimation method (CMEBE) [4] derives an optimal frame length about the number of tags and the probability of capture effect for the dynamic frame length ALOHA protocol. Based on the frame length, CMEBE achieves an optimal value of the identification efficiency. However, the algorithm requires two-dimensional (2D) searches to estimate the number of tags and the probability of capture effect. When the range of the searches is too large, the computational complexity will increase.

In this letter, we propose a capture-aware estimation (CAE) algorithm for a dynamic frame length ALOHA protocol. The proposed algorithm firstly estimates the number of tags from the number of idle slots in a frame. And then, the algorithm estimates the probability of capture effect. From these parameters, an optimal frame length can be obtained. In the proposed algorithm, the estimation does not require the 2D searches. Computer simulation results show that the identification efficiency of CAE is higher than Optimal Q and GBT and almost identical to CMEBE. Furthermore, the estimation error of CAE is lower than 4%, which is close to CMEBE. The advantage of CAE is that it does not need many steps to search an extreme value. It thus reduces the computational complexity.

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II. System Model and Problem Description

A dynamic frame length ALOHA RFID protocol [1, 4, 5] configures an identification cycle with some continuous frames that consist of slots. Each tag responds at a random slot and only once in a frame. For a given slot, there are only three probable outcomes: no tags, only one tag and at least two tag responses in a slot, respectively. If no capture effect happens, the three outcomes mean an idle slot, a collision slot and a successful slot, respectively. If capture effect happens, however, two or more than two tag responses may produce a successful slot. In the protocol, all collided tags and hidden tags in a current frame will enter the next frame to be identified again. When all tags in a readers range are successfully identified, the identification cycle is finished. In order to reduce the idle slots and collision slots, the dynamic frame length ALOHA protocol will dynamically adjust each frame length. Therefore, the protocol has higher identification efficiency than a fixed framed ALOHA protocol. Now, we give the following definitions for the protocol under capture effect.

Definition 1: If l denotes the ith frame length in the dynamic frame length ALOHA protocol, the frame length can be defined by

$$l := c_0 + c_1 + c_k \tag{1}$$

where c_0, c_1 and c_k denote the observed number of idle slots, successful slots and collision slots, respectively in the ith frame.

Definition 2: Let p denote the occurrence probability of capture effect in the ith frame. Then p can be defined by

$$p := s/a'_k, a'_k \neq 0 \tag{2}$$

where s denotes the expected number of slots in which capture effect happens in the ith frame, and a'_k denotes the expected number of slots in which at least two tags respond in the ith frame.

Definition 3: Let P_e denote the identification efficiency of the ith frame. Then P_e is defined by

$$P_e := c_1/l \tag{3}$$

The dynamic frame length ALOHA protocol needs the information of the probability capture effect and the number of tags to adjust a frame length. In general, the information is unknown for a reader. CMEBE proposed in [4] estimates the information by

$$(\hat{p}_{\text{CMEBE}}, \hat{n}_{\text{CMEBE}}) = \underset{p \in P, n \in N}{\arg\min} \|\mathbf{E}(p,n) - \mathbf{O}\|^2 \tag{4}$$

where
$\| \bullet \|$ is an Euclidean norm,
$\mathbf{O} = [c_0, c_1, c_k]^T$,
$\mathbf{E}(p,n) = [a_0, a_1, a_k]^T$,
a_0, a_1 and a_k denote the expected number of idle slots, successful slots and collision slots in the ith frame, respectively when the probability of capture effect is p and the number of tags is n,
P and N are sets defining the search space w.r.t. the probability of capture effect p and the number of tags n, respectively.

Eq. (4) needs to compute the values of a_0, a_1 and a_k.From *Definition 2*, the values can be given by [2, 4]

$$a_0 = a'_0 \tag{5-a}$$

$$a_1 = a'_1 + pa'_k \tag{5-b}$$

$$a_k = (1-p)a'_k \tag{5-c}$$

where a'_0, a'_1 and a'_k denote the expected numbers of slots where no tag, only one tag and at least two tags respond in the ith frame, respectively.The derivation of a'_0, a'_1 and a'_k is as follows. Given one of the slots, n tags allocated in the slot are a binomial distribution with n Bernoulli experiments and $1/l$ success probability. The probability of r tags responding in the slot is therefore given by [1, 3, 5]

$$p(l,n,r) = \binom{n}{r}(\frac{1}{l})^r(1-\frac{1}{l})^{n-r} \tag{6}$$

And then, the expected number of the slots where 0, 1 and $k(k>1)$ tags respond simultaneously can be given by

$$a'_0 = l(1-\frac{1}{l})^n \tag{7-a}$$

$$a'_1 = n(1-\frac{1}{l})^{n-1} \tag{7-b}$$

$$a'_k = 1 - a'_0 - a'_1 \tag{7-c}$$

respectively. Thus we will obtain the value of a_0, a_1 and a_k from (5) and (7). Based on *Definition 3* and (7), the expected identification efficiency in the ith frame is given by

$$P_e = \frac{n(1-1/l)^{n-1} + p[l - l(1-1/l)^n - n(1-1/l)^{n-1}]}{l} \tag{8}$$

In order to obtain the maximum identification efficiency, we let $dP_e/dl = 0$ and thus have the optimal frame length [4]

$$l_{opt} = p + (1-p)n \tag{9}$$

From (4), CMEBE needs 2D searches for the number of tags and the probability of capture. If the cardinality of P and N is large, the number of the searches is also large and thus the computational complexity will be high. Next, we will propose our CAE algorithm, which does not require searching an extreme value.

III. CAE ALGORITHM

A. Estimation algorithm

As capture effect has no affect on idle slots, the number of tags will be estimated from the number of idle slots. From (5-a) and (7-a), we have

$$a_0 = l(1-1/l)^n$$

Substituting $a_0 = c_0$ into the formula above, we estimate the number of tags in the ith frame by

$$\hat{n} = \frac{ln(c_0/l)}{ln(1-1/l)}, c_0 \neq 0 \tag{10}$$

The probability of capture effect p is estimated from the observed and expected numbers of successful slots and collision slots, based on the following mathematical formulation. From (5), we have

$$\mathbf{A}p = \mathbf{C} + \mathbf{\Xi} \tag{11}$$

where
$\mathbf{A} = [\hat{a}'_k, \hat{a}'_k]^T$,
$\hat{a}'_k$ and $\hat{a}'_1$ are obtained by substituting the estimated number of tags $\hat{n}$ into (7),
$\mathbf{C} = [c_1 - \hat{a}'_1, \hat{a}'_k - c_k]$,

$\mathbf{\Xi} = [\xi_1, \xi_2]^T$ which denotes an error vector.
Thus the probability of capture effect of the ith frame can be given by least-squares estimation, yielding

$$\hat{p} = \mathbf{A}^{\dagger} + \mathbf{C} \tag{12}$$

where $\mathbf{A}^{\dagger}$ denotes the pseudo inverse of $\mathbf{A}$.

B. Setting frame length and pseudo-code of algorithm

After estimating the number of tags and the probability of capture effect, we can set an optimal frame length. We assume that the probability of capture effect in the $i+1$th frame p_{next} is a function about p, i.e. $p_{next} = f(p)$. The number of unidentified tags in the $i+1$th frame is $n_{next} = n - c_1$. From (9), the optimal length of the $i+1$th frame can thus be set to

$$l^*_{next} = f(\hat{p}) + [1 - f(\hat{p})](\hat{n} - c_1) \tag{13}$$

Generally, the function $f(\bullet)$ is not easy to be obtained. It is related to not only the frame length but also the environment of identification, such as distance between each tag and a reader and strength of each tags back-scattering signal [2, 3]. In order to facilitate the analysis of the optimal length, we adopt a simplified model of simulation experiments in [2-4], $p_{next} = p, \forall i$. That is, the probability of capture effect in each frame is a constant. Here, we give the pseudo-code of CAE algorithm.

```
dynamicALOHA(l)
  repeat
    {c0 = 0, c1 = 0, ck = 0
    interrogate(l)
    for slot = 1 to l do
      receive tag responses
      if detect only one tag response then
        tagIdentification() and c1 ++
      end if
      if detect tag collision then
        ck ++
      end if
      if detect no tag responses then
        c0 ++
      end if
    end for
    [n, p]=PerformEstimate(l, c0, c1, ck);
    // estimating by (10) and (12)
    l=SetLength(n, p, c1); // optimal length by (13)}
  until (c1 = 0 and ck = 0)
```

C. Analysis of computational complexity

Some conventional estimates for the number of tags, such as Vogt estimate [1], need to step-by-step search an extreme value in a range of the number of tags. And, CMEBE proposed in [4] requires the 2D searches for the number of tags and the probability of capture effect. Assume $u = |P|, \nu = |N|$, where $| \bullet |$ denote the cardinality of a set. And then, the number of brute searches for CAEBE is $u\nu$. Instead of searching, CAE one-step estimates the number of tags by (10) and the probability of capture effect by (12), respectively. A comparison of the number of searches among Vogt, CMEBE and CAE algorithm is given in Table I. Next, we will analyze the computational complexity of the algorithms.

Definition 4: Let $f(x)$ and $g(x)$ be two functions defined on some subsets of the real numbers. One writes

$$f(x) = O(g(x)) \tag{14}$$

TABLE I
COMPUTATIONAL COMPLEXITY OF VOGT, CMEBE AND CAE

Method	Estimation	Number of brute searches	Computational Complexity
Vogt	n	ν	$O(\sum_{j=1}^{\nu} \tilde{n}_j)$
CMEBE	p, n	$u\nu$	$O(u\sum_{j=1}^{\nu} \tilde{n}_j)$
CAE	p, n	1	$O(\hat{n})$

as $x \to \infty$ if and only if there exists a positive real number M and a real number x_0 such that $|f(x)| \le M|g(x)|$ for all $x > x_0$.

From (4), let

$$\varepsilon_j = \|\mathbf{E}(\tilde{p}_j, \tilde{n}_j) - \mathbf{O}\|^2$$

where $\tilde{p}_j$ and $\tilde{n}_j$ are the jth searching value of the probability of capture effect and the number of tags, respectively. The number of multiplication that the computation of ε_j requires is $\tilde{n}_j$. Hence the computational complexity of ε_j can be denoted as $O(\tilde{n}_j)$ from (14). Since (4) needs $u\nu$ brute searches, CMEBE's computational complexity can be denoted as

$$\text{CMEBE} : O(u\sum_{j=1}^{\nu} \tilde{n}_j) \tag{15}$$

On the other hand, the number of multiplication that the computation of $\hat{p}$ in (12) requires is $\hat{n}$. Likewise the computational of $\hat{p}$ is denoted as $O(\hat{n})$ from (14). The computational complexity of (10) is a logarithmic class which is trivial, compared with the exponential class in (12). Thus the majority of CAE algorithms computational complexity will be on (12), and CAE algorithms complexity can be approximately denoted as

$$\text{CAE} : O(\hat{n}) \tag{16}$$

A comparison of the computational complexity among Vogt, CMEBE and CAE algorithm is also given in Table I.

IV. SIMULATION RESULTS

This section gives the computer simulation results of CAE, CMEBE, GBT and Optimal Q algorithms. We individually perform each simulation 5000 times and average the 5000 simulation results into the final results. In the simulation, the probability of capture effect adopts the model in [2-4], i.e. $p_{next} = p, \forall i$. In CMEBE algorithm, the set of number of tags and the probability of capture effect are $N = \{c_1 + 2c_k \le n \le N_{max} | n \in Z\}$ where $N_{max} = 500$ and $P = \{0, 0.1, \cdots, 1.0\}, \forall i$,respectively. In Optimal Q algorithm, we assume that the number of tags n, $\forall i$ will be known beforehand [3] and not be estimated.

Fig. 1 shows the estimation error of p and n_0 in the first frame for CAE and CMEBE, where the error is given by

$$e = |\frac{\hat{x} - x}{x}| \times 100\% \tag{17}$$

in which x is a representation of p or n_0, and n_0 denotes the number of unidentified tags in the beginning of the first frame. In Fig.1, $n_0 = 300$ and the initial frame length is set to

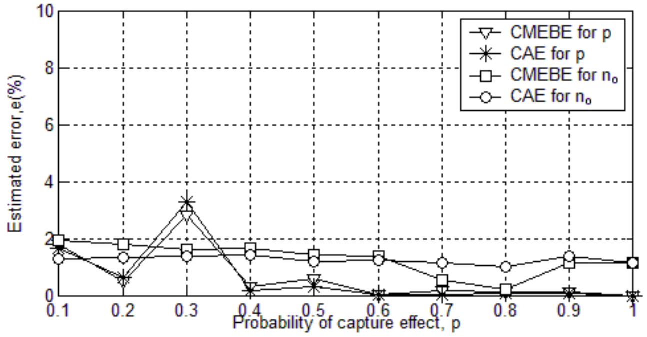

Fig. 1. Simulation results: estimation error, $0.1 \le p \le 1$.

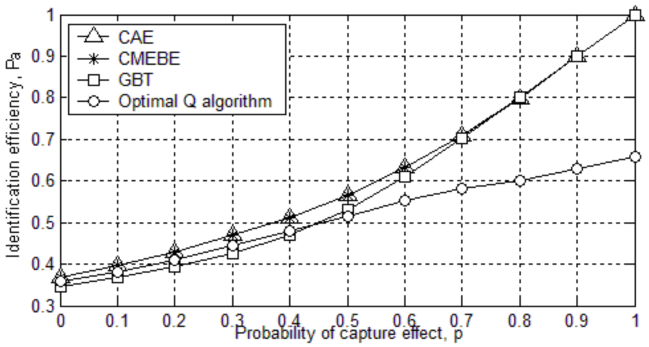

Fig. 2. Simulation results: identification efficiency, $0 \le p \le 1$.

$l_0 = 128$. It is seen from Fig.1 that the estimation error of CAE is less than 4% and is nearly identical to CMEBE. Fig. 2 shows the identification efficiency curves for CAE, CMEBE, GBT and Optimal Q algorithms, respectively when the probability of capture effect varies from 0 to 1. Likewise, we let $n_0 = 300$ and $l_0 = 128$ in Fig. 2. And, the identification efficiency P_a is the average value while all tags identified, i.e.

$$P_a = n_0/L \tag{18}$$

where L is the sum of all frames' length. From Fig. 2, we see that the CAE's efficiency is higher than GBT and Optimal Q algorithms, and CAE has almost the same curve as CMEBE.

Fig. 3 shows the number of searches for estimation of p and n_0 in the first frame. In Fig. 3, we let $l_0 = 128$ and the probability of capture effect p varies from 0 to 1. Since CAE requires no searches, it is seen from Fig.3 that the number of searches in CMEBE is much larger than those in CAE regardless of the number of tags n_0 or the probability of capture effect$p$. Table II also gives the computational complexity of CAE and CMEBE which choose the same system parameters as Fig. 3. The data in Table II is computed from Table I. From Table II's results, CAE has lower complexity than CMEBE, regardless of the value of n_0 and p.

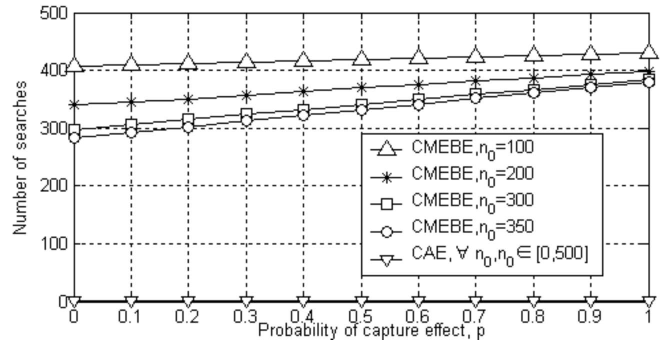

Fig. 3. Simulation results: the number of searches, $0 \le p \le 1$.

TABLE II
SIMULATION RESULTS: COMPUTATIONAL COMPLEXITY, $0 \le p \le 1$

Method	$p = 0.1$	$p = 0.5$	$p = 0.9$
CMEBE, $n_0 = 100$	1332705	1338016	1349634
CMEBE, $n_0 = 200$	1199495	1284085	1314192
CMEBE, $n_0 = 300$	1171819	1305414	1292500
CAE, $n_0 = 100$	99	100	99
CAE, $n_0 = 200$	200	200	201
CAE, $n_0 = 300$	303	303	303

V. CONCLUSION

In this letter, we propose the CAE algorithm to optimize the identification efficiency of the RFID dynamic frame length ALOHA protocol under capture effect. The identification efficiency that the CAE algorithm achieves is higher than the existing GBT and Optimal Q algorithm and almost identical to the CMEBE algorithm, but the CAE algorithm has lower computational complexity than the CMEBE algorithm.

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