Capture-Aware Estimation for Large-Scale RFID Tags Identification

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***Abstract*—How to estimate the number of passive radio frequency identification (RFID) tags and the occurrence probability of capture effect is very important for a dynamic frame length Aloha RFID system with capture effect. The estimation would relate to setting an optimal frame length, which makes tag identification achieve higher efficiency. Under large-scale tags identification environment, the number of tags may be much greater than an initial frame length. In this scenario, existing estimates do not work well. In this letter, we propose a novel estimation method for the large-scale tags identification. The proposed method could adjust the initial frame length matched to the number of tags from only the first several slots in the frame. The advantage of the proposed method is to work better even when the number of tags is much greater. Numerical results show that, the proposed method has lower estimation errors under the large-scale tag identification. After setting an optimal frame length from the estimated results of the proposed method, furthermore, we could obtain higher identification efficiency.**

***Index Terms*—Aloha, capture effect, estimation, RFID.**

I. Introduction

PASSIVE RADIO FREQUENCY IDENTIFICATION (RFID) can support simultaneous multi-tag identification and hence offer 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 two or more than two tags backscatter their signals to the reader simultaneously, collision may happen and will disturb the identification. However, two or more than two tags do not necessarily lead to the collision. Since the distances between the tags and the reader are different, the strengths of the backscattered signals are different. The stronger tag would be identified, and the weaker one would be hidden [1]. The phenomenon is called capture effect [2]. In recent years, how to optimally solve the collision under capture effect has attracted much attention [1], [3], [4].

Dynamic frame length Aloha algorithm [2]–[4] is very popular for RFID tags anti-collision. In the algorithm, an optimal frame length could make tag identification obtain optimal efficiency. Setting the optimal frame length requires the information of the number of tags and the occurrence probability of capture effect [3]. Therefore, how to estimate the information is very important for the optimal efficiency. Vogt algorithm [2] estimates the number of tags by searching a minimum value for distances between observed and expected results in a frame. When the capture effect occurs, however, Vogt could not obtain the optimal identification efficiency since the algorithm does not consider the probability of capture effect affecting the optimal frame length. Capture-aware backlog estimation method (CMEBE) [3] derives an optimal frame length about the number of tags and the probability of capture effect, and the two values are estimated from a two-dimensional (2D) search for a minimum value. However, the number of tags may be much greater than an initial frame length under large-scale tag identification environment, which means there are hundreds of tags or more in the magnetic field of a reader at the same time. This will cause that the minimum value does not exist at all. Capture-aware estimation (CAE) [4] could also estimate the number and the probability simultaneously. Compared with CMEBE, CAE's computation complexity is lower owing to no searches for a minimum value. However, CAE is still difficult to be applied to the large-scale tags identification environment. When the number of tags is much greater than an initial frame length, CAE may have a trouble to figure out a logarithm of zero.

In this letter, we propose a novel estimate method for the large-scale RFID tag identification with capture effect. The main contributions of our work are as follows. First, the proposed estimate method could be applied to the large-scale RFID tags identification environment. Second, the proposed method applies a minimum mean square error (MMSE) rule to estimate the number of tags and the probability of capture effect simultaneously. Third, we derive an optimal frame length, which is compatible with EPC C1 Gen 2 standard [6]. From numerical results, the proposed method has lower estimation errors and obtains higher identification efficiency under the large-scale tags identification with capture effect.

II. Identification Efficiency and Estimation Problem

A dynamic frame length Aloha RFID algorithm [2]–[4] 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

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a slot, respectively. If no capture effect happens, the three outcomes mean an idle slot, a successful slot and a collision slot, respectively. If capture effect happens, however, two or more than two tags responses may produce a successful slot. In the algorithm, all collided tags and hidden tags in a current frame will enter the next frame to be identified again. When all tags in a reader's range are successfully identified, the identification cycle is finished. In order to reduce the idle slots and collision slots, the dynamic frame length Aloha algorithm will dynamically set each frame length. Therefore, the algorithm has higher identification efficiency than a fixed framed Aloha algorithm. If t_0, t_1 and t_k denote the duration of an idle, successful and collision slot, respectively, the expected identification efficiency of a frame in the dynamic Aloha can be defined as [2]

$$P_s = a_1 t_1/(a_0 t_0 + a_1 t_1 + a_k t_k) \tag{1}$$

where a_0, a_1 and a_k ($k \geq 2$) denote the expected number of idle, successful and collision slots, respectively and could be given by [3]

$$a_0 = a_0' \tag{2a}$$
$$a_1 = a_1' + \alpha a_k' \tag{2b}$$
$$a_k = (1-\alpha) a_k' \tag{2c}$$

in which α denotes the probability of capture effect, a_0', a_1' and a_k' are the expected number of slots where no tags, one tag and at least two tags response, respectively. From [2]–[4], a_0', a_1' and a_k' can be given by

$$a_0' = l(1-1/l)^n \tag{3a}$$
$$a_1' = n(1-1/l)^{n-1} \tag{3b}$$
$$a_k' = l - l(1-1/l)^n - n(1-1/l)^{n-1} \tag{3c}$$

where l denotes the frame length and n denotes the number of tags. Substituting (2) and (3) into (1), we can find that P_s is in fact a function about n and α. Generally, the values of n and α are unknown in advance. Therefore, we need to estimate them.

Vogt algorithm [2] estimates the number of tags from

$$\hat{n}_{Vogt} = \min_{n \in \mathrm{N}} \|\mathbf{E}'(n) - \mathbf{O}\|^2 \tag{4}$$

where $\| \bullet \|$ is an Euclidean norm, $\mathbf{E}'(n) = [a_0', a_1', a_k']^{\mathrm{T}}$, $\mathbf{O} = [c_0, c_1, c_k]^{\mathrm{T}}$, c_0, c_1 and c_k denote the observed numbers of idle, successful and collision slots, respectively and N denotes the search range of the number of tags. In (4), Vogt only estimates the number of tags n and does not consider the probability of capture effect α. It sets the frame length by $l = n$ [2]. From [3], Vogt is difficult to obtain the maximum identification efficiency without α.

CMEBE algorithm [3] estimates the number of tag and the probability of capture effect by

$$(\hat{\alpha}_{CMEBE}, \hat{n}_{CMEBE}) = \underset{\alpha \in \mathrm{A}, n \in \mathrm{N}}{\arg\min} \|\mathbf{E}(\alpha, n) - \mathbf{O}\|^2 \tag{5}$$

where $\mathbf{E}(\alpha, n) = [a_0, a_1, a_k]^{\mathrm{T}}$, A and N denote the search range of α and n, respectively. From (5), CMEBE needs the 2D searches for a minimum value of $\|\mathbf{E}(\alpha, n) - \mathbf{O}\|^2$. Under large-scale tags identification environment, the number of tags may be much greater than an initial frame length, and the number of idle slots c_0 in the frame is likely zero. In this scenario, $\|\mathbf{E}(\alpha, n) - \mathbf{O}\|^2$ in (5) may not have a minimum value. Let

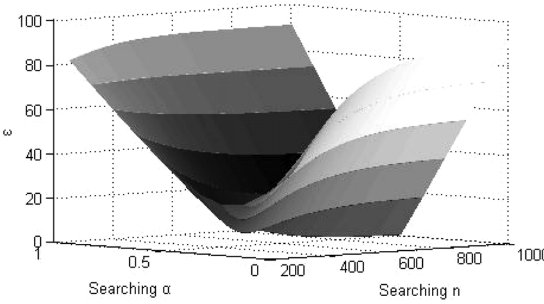

Fig. 1. ε in (6) about searching number of tags and probability of capture effect when $l = 128$ and $n = 800$.

$$\varepsilon = \|\mathbf{E}(\alpha, n) - \mathbf{O}\|^2 \tag{6}$$

We give a three-dimensional surface of ε about searching α and n in Fig. 1. In the figure, the initial frame length is 128, the number of tags number is 800 and the probability of capture effect is 0.5. From Fig. 1, the canyon of the curve surface ε decrease monotonously with n. There is not a global minimum value of ε at all.

CAE algorithm estimates the number of tags by

$$\hat{n}_{CAE} = \ln(c_0/l)/\ln(1-1/l) \tag{7}$$

and then estimates the probability of capture effect from (2) [4]. Since (7) does not need to search a minimum value like Vogt and CMEBE, CAE has lower computational complexity. When the number of tags is much greater than an initial frame length, however, the number of idle slots is likely $c_0 = 0$ and we would not figure out $ln(c_0/l)$ in (7). Thus, CAE is also difficult to be applied to the large-scale tags identification. Next, we will propose our estimation method. The proposed method would accurately estimate the number of tags and the probability of capture effect even when the number of tags is much greater.

III. Estimation for Large-Scale Tag Identification

From the analysis in Section II, the reason why CMEBE and CAE are not applied to the large-scale tags identification is $n >> l$ and then $c_0 = 0$. Intuitively, we can lengthen the frame length l until $c_0 \neq 0$. However, how can we obtain c_0? Generally, c_0 is obtained only after the frame completing. If $n >> l$, there will produce many collision slots after the frame completing. This will cause lower identification efficiency. Actually, we could predict whether $c_0 = 0$ or not from only the first several slots in the frame. Hence, excessive collision slots would be reduced. Next, we will illuminate the method.

Given one of slots in a frame of l, the probability that the slot is idle, successful and collision can be shown as

$$p_j = a_j/l \tag{8}$$

where $j = 0$, 1 and $k \geq 2$, respectively. A non-idle slot is either successful or collision. For the first m non-idle slots, the number of collision slots will be $m-i$ if the number of successful slots is i. Then, the probability of i successful slots and $m-i$ collision slots is $\binom{m}{i} p_1^i p_k^{m-i}$. Thus, the probability that the first m slots in a frame are all non-idle is given by

$$P_m = \sum_{i=0}^{m} \binom{m}{i} {p_1}^i {p_k}^{m-i} \tag{9}$$

TABLE I
PROBABILITY THAT ALL OF THE FIRST m SLOTS ARE NON-IDLE WHEN $l = 128$

n	m=1	m=2	m=3	m=4	m=5
100	0.543 (0.544)	0.293 (0.296)	0.160 (0.161)	0.085 (0.087)	0.046 (0.048)
300	0.905 (0.905)	0.819 (0.819)	0.741 (0.741)	0.670 (0.671)	0.606 (0.607)
500	0.980 (0.980)	0.960 (0.961)	0.941 (0.942)	0.923 (0.923)	0.904 (0.905)
700	0.996 (0.996)	0.992 (0.992)	0.998 (0.998)	0.983 (0.984)	0.980 (0.980)
1000	1.000 (1.000)	0.999 (0.999)	0.999 (0.999)	0.998 (0.998)	0.998 (0.998)

where the values given in the brackets are computed from (9)

Not that (9) could also be written as $(1-p_0)^m$ from binomial theorem. Thus, it is not related to the value of α. Table I gives the theoretical and experimental values of P_m, $m = 1, 2, 3, 4$ and 5 when $l = 128$ and n varies from 100 to 1000. In the experiments, a reader sends a query command and then the tags response randomly in slots. The theoretical values are from (9) and the experimental ones are from n_n/n_t where n_n is the number of the experiments where the first m slots are all non-idle and n_t is the total number of the experiments. Here, we individually perform the experiments 250000 times. From the table, all of P_m will increase with n, regardless of m. Especially, P_m is very close to 1 when $n = 1000$. The result shows that all of the first m slots in a frame are likely non-idle when the number of tags n is much greater than the frame length. Thus, we could adjust the frame length from only the first m slots. If the first slots are all non-idle, the adjusted frame length can be given by

$$l_{next} = Kl \tag{10}$$

where K is a number that should be greater than one. Note that we judge whether the first m slots are all non-idle instead of being all collision like the method in [5]. The reason is that capture effect may occur in a slot even if the slot has more than two tag responses.

IV. MMSE ESTIMATE AND OPTIMAL FRAME LENGTH

In this section, we apply an MMSE rule to estimate the number of tags and the probability of capture effect simultaneously. The MMSE estimation should meet

$$\langle \hat{n}, \hat{\alpha} \rangle = \min_{\hat{n}\in \mathrm{N}, \hat{\alpha}\in \mathrm{A}} \mathrm{E}\{(n-\widehat{n})^2 + (\alpha - \widehat{\alpha})^2\} \tag{11}$$

which is equivalent to

$$\langle \hat{n}, \hat{\alpha} \rangle = \min_{\hat{n}\in \mathrm{N}, \hat{\alpha}\in \mathrm{A}} \sum_n \sum_\alpha [(n-\widehat{n})^2 + (\alpha - \widehat{\alpha})^2] p(n, \alpha, C) \tag{12}$$

where $\mathrm{N} = \{c_1 + 2c_k \le \hat{n} \le N_{\max}\}$ and $\mathrm{A} = \{0 \le \hat{\alpha} \le 1\}$ denote the ranges of the number of tags and the probability of capture effect respectively, $p(n, \alpha, C)$ denotes the joint probability of n, α and $C = \langle c_0, c_1, c_k \rangle$. From Bayesian rules, we have $p(n, \alpha, C) = p(n, \alpha|C)p(C)$ where the conditional probability can be given by [7]

$$p(n, \alpha|C) = \frac{l}{c_0! c_1! c_k!} (p_0)^{c_0} (p_1)^{c_1} (p_k)^{c_k} \tag{13}$$

Let the first derivatives of (12) w.r.t. $\hat{n}$ and $\hat{\alpha}$ be zero, respectively and then we have

$$\hat{n} = \sum_n \sum_\alpha n \bar{p}(n, \alpha|C) \tag{14a}$$

$$\hat{\alpha} = \sum_n \sum_\alpha \alpha \bar{p}(n, \alpha|C) \tag{14b}$$

where $\bar{p}(n, \alpha|C) = p(n, \alpha|C)/\Sigma_n \Sigma_\alpha p(n, \alpha|C)$.

Under capture effect, the optimal frame length w.r.t. n and α is derived in references [3], which assumes that the durations of an idle, a collision and a successful slot are identical. However, RFID systems such as EPC C1 Gen2 standard specify that the durations of the three slots are different. Next, we will derive the optimal frame length compatible with EPC C1 Gen2.

Consider a linear model, $l = rn$[8]. Substituting (2) and (3) into (1) and letting $\beta = t_0/t_1$, $\gamma = t_k/t_1$, we have

$$P_s \approx \frac{e^{-\frac{1}{r}}\left(\frac{1-\alpha}{r} - \alpha\right) + \alpha}{e^{-\frac{1}{r}}\{\frac{1}{r} - (1+\frac{1}{r})[(1-\alpha)\gamma + \alpha] + \beta\} + (1-\alpha)\gamma + \alpha} \tag{15}$$

where $\lim_{n\to+\infty}(1 - 1/rn) = e^{-1/r}$. Let

$$r^* = \arg\max_{r\in \mathrm{R}} P_s \tag{16}$$

where R denotes the searching range of r. Then, the optimal frame length can be expressed by

$$l^* = \lfloor r^* n \rfloor \tag{17}$$

where $\lfloor \cdot \rfloor$ denotes a floor integer function.

In summary, we give the proposed method as follows.

1. Initialize a frame length $l = l_0$;
2. A reader transmits a query command with l, and tags will select random slots in the frame to respond;
3. If the first m slots are all non-idle, we let $l = l_{next}$ in (10) and then go to step 2. If not, go to step 4;
4. Complete the frame, and count the numbers of idle slots, successful slots and collision slots in the frame. And then, estimate the number of tags and the probability of capture effect by (14) and set the optimal frame length by (17).

V. NUMERICAL RESULTS

In this section, we give numerical results to verify the performance of the proposed estimate method. The experimental results are the average results of 500 independent experiments. We implement the experiments by M-files in MATLAB R2012a. In the experiments, we consider a scenario with a single reader and a set of passive tags that enter the reader's zone and do not leave until all the tags are successfully identified. The other experiment parameters are as follows.

- An initial frame length is $l_0 = 128$.
- The search range of the number of tags is $\mathrm{N} = \{c_1 + 2c_k \le n \le N_{\max} | n \in \mathrm{Z}\}$ where $N_{\max} = 1000$, and the search range of the probability of capture effect is $A = \{0.1, 0, 2, \ldots 1.0\}$.
- The parameter m in (9) is set to 3. From Table I, when m is smaller, the frame length would be likely to be lengthened although n is close to l, e.g. $P_m = 0.54$ when $m = 1$ and $n = 100$. On the other hand, when m is larger, the frame length would be likely to be unchanged although n is larger than l, e.g. $P_m = 0.60$ when $m = 5$ and $n = 300$. Here, $m = 3$ is a compromise.
- The parameter K in (10) is set to 2. When n is much larger than l, we expect l_{next} to increase as soon as possible and K should be a larger number. If the value of K is too large, however, l_{next} would be likely a much larger number than n. In this case, there are many idle slots produced. Since

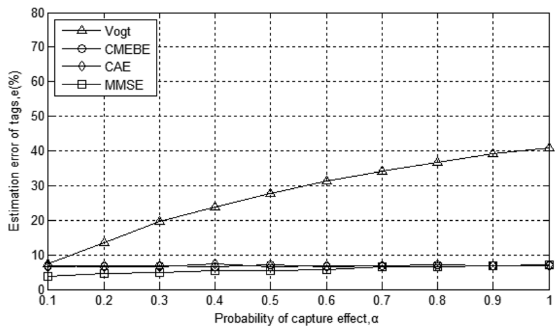

Fig. 2. Estimation error in (18) when $l = 128$, $n = 200$, $K = 2$ and $m = 3$.

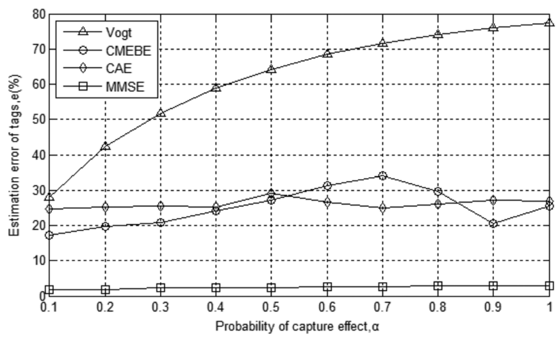

Fig. 3. Estimation error in (18) when $l = 128$, $n = 600$, $K = 2$ and $m = 3$.

the maximum value of n is set to 600 in the experiments, $K = 2$ is also a compromise.

- From EPC C1 Gen2 [6], durations of an idle, successful and collision slot are set $t_0 = 50$ μs, $t_1 = 400$ μs and $t_k = 200$ μs, respectively.

Fig. 2 shows the estimation errors e of the number of tags for Vogt, CMEBE, CAE and MMSE, respectively when $n = 200$ and the probability varies from 0.1 to 1. And, e is defined by

$$e = |(\hat{n} - n)/n| \times 100\% \quad (18)$$

In the figure, MMSE denotes the algorithm estimating the number of tags in (14). From Fig. 3, the curves are very close to each other and approximately between 5% and 8% except Vogt. The results show that CMEBE, CAE and MMSE could estimate the number of tags better when the number is not much larger than the frame length. In addition, Vogt has higher estimation errors due to considering no capture effect.

Fig. 3 shows the estimation errors e of the four algorithms above when $n = 600$ and the other parameters choose the same as Fig. 2. From the figure, CMEBE and CAE's curves fluctuate between 20% and 35%, while MMSE is only about 4% and much lower than the two former algorithms. The reason is that when the number of tags is much greater than the frame length, the number of idle slots may be zeros. In this scenario, there is not a minimum value for CMEBE, and the searching result would be an upper value of the search range according to Fig. 1. And, CAE also fails to accurately estimate the number since the result of (7) will be ∞. Of course, the actual number could not be infinite. Here, we let the estimated value be $N_{\max}$.

Next, we will give the identification efficiency of the four algorithms above. The algorithms use the estimated results in

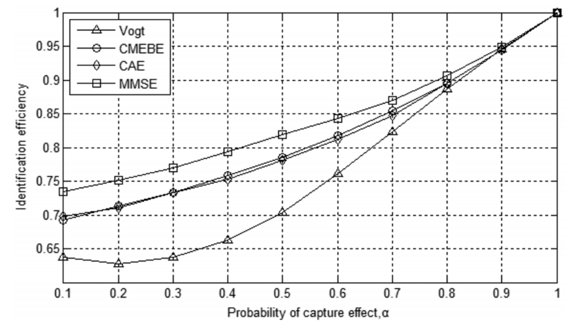

Fig. 4. Identification efficiency when $l = 128$, $n = 600$, $K = 2$ and $m = 3$.

Fig. 3 to set their frame length. Vogt's optimal frame length is set to n[2], CMEBE and CAE's optimal length is set to $\alpha + (1 - \alpha)n$[3], [4], and MMSE's optimal length is set from (15-17). After setting the frame length, we implement experiments to obtain the identification efficiency in the frame, where the other parameters also choose the same as Fig. 3. The results of the efficiency are shown in Fig. 4. It can be seen that the curve of MMSE is higher than those of the others. The reason is that MMSE has lower estimation errors than the others. Furthermore, MMSE sets the optimal frame length from (17).

VI. Conclusion

In this letter, we propose a novel estimate method for the large-scale RFID tags identification with capture effect. When the number of tags is much greater than an initial frame length, the proposed method has lower estimation errors than the existing Vogt, CMEBE and CAE algorithm. Using the estimated results by the proposed method to set an optimal frame length, furthermore, we could obtain higher identification efficiency than the existing algorithms.

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