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A Novel Cross Layer Anti-Collision Algorithm for Slotted ALOHA-Based UHF RFID Systems

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ABSTRACT Reducing collisions in UHF RFID systems is a crucial problem. In most anti-collision designs, the reader has to estimate the number of tags within its reading range during the interrogation process. Most of the approaches estimate the number of tags with observations in multiple time slots. Since estimation error varies along with the initial frame length and the number of tags, system efficiency is affected by both of them. To reduce the sensitiveness to them and improve system efficiency, we propose a novel MAC-PHY cross-layer anti-collision algorithm based on Bayesian inference. Specifically, each frame is allowed to end at an early stage and a slot-by-slot estimator is proposed. Benefit from its slot-by-slot nature, system efficiency is more stable and independent on the initial frame length and very close to the upper bound of dynamic framed slotted ALOHA (DFSA) algorithm. The performance of the proposed method is compared with the state-of-the-art algorithms through numeric simulations. The results show that the proposed solution significantly outperforms the compared ones.

INDEX TERMS Anti-collision, Bayesian estimate, cross-layer, UHF RFID.

I. INTRODUCTION

Anti-collision algorithms are carried out in multi-access UHF RFID systems to reduce collisions as well as to increase channel efficiency. As one of the most popular anti-collision algorithms for RFID systems, dynamic framed slotted ALOHA (DFSA) algorithm employs a mechanism similar to time division multiple access (TDMA). A frame is defined as a series of time slots for random access. The number of time slots in one frame is defined as frame length. The reader dynamically adjust frame length frame by frame. The system efficiency of a RFID system is usually defined as the ratio of the number of successfully identified tags over the total number of used slots. It is well known that DFSA reaches its optimal system efficiency when the number of slots equals to the number of tags those are waiting to be identified [1]. Intuitively, with perfect information of the number of tags, optimal system efficiency is easily obtained. However, the number of tags is unknown and required to be estimated during interrogation process.

Usually, slots in each frame are divided into three types (empty, successful and collided) and the number of tags is estimated based on the types of observed slots. The estimation accuracy strongly depends on the number of observed slots. When the frame length is periodically updated frame by frame, it is obvious that one can estimate the number of tags with all slots in a frame, which is called frame by frame (FbF) estimator. However, when the frame length does not match the number of tags, the estimation error is relatively high and there is no chance for the reader to adjust frame length before the frame runs out. As a result, the system efficiency degrades. An early break policy is introduced into DFSA to give readers more chances to adjust frame length, which is called slot-by-slot (SbS) estimator. In this kind of method, the reader estimates the number of tags in the middle of a frame and stops it when the frame length is not optimal. After

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that, a new frame is set up. The sensitiveness to the initial frame length and the number of tags are significantly reduced. However, most state-of-the-art SbS estimators are modified from FbF estimators, requiring multiple slots from one frame to make decisions and the accuracies of them are affected by the number of observed slots. In every new frame, the reader has to wait for enough time slots for acceptable accuracy of estimation. To further reduce the sensitiveness, a complete SbS estimator utilizing more chances to update frame length is required. Besides, the estimation needs to be carried out in each time slot. Thus, the computation complexity and time delay are important.

In this paper, we consider slotted ALOHA-based system as a special DFSA in which every frame is early stopped after the first slot. A cross layer anti-collision algorithm (CLAA) is proposed. This algorithm consists of a modified Bayesian inference algorithm estimating the number of all tags in MAC layer and a clustering algorithm estimating the number of tags in single time slot in physical layer. The contributions of this work are twofold. First, a complete SbS estimator is proposed based on Bayesian inference. Compared with the existing approaches, the proposed one's accuracy does not degrade when a new frame is set up. Thanks to its slot-by-slot nature, the system efficiency is improved and sensitive to the initial frame length and the number of tags is significantly reduced. Second, the computation requirement in MAC layer is reduced to fixed number of floating-point operations in each time slot, which is close to that of ILCM. Although an extra physical layer algorithm is required, it could be implemented in hardware with a faster and more stable way. Simulation results verify the effectiveness of CLAA and the system efficiency outperforming the state-of-the-art DFSA algorithms.

The rest of this paper is organized as follows. Related works are reviewed in Section II. The detailed design of cross layer anti-collision algorithm is provided in Section III. In Section IV, the proposed algorithm is evaluated and compared with the state-of-the-art DFSA algorithms through numeric simulations. Finally, conclusion follows.

II. RELATED WORK

Existing anti-collision algorithms in MAC layer can be classified into DFSA [1]–[14], tree-based algorithms [15]–[17] and binary splitting (BS) based algorithms [18], [19]. Tree-based algorithms and BS algorithms are operated by recursively dividing responding tags into smaller subsets until each subset has only one or zero tag, which is quite different from DFSA. Therefore, these researches are not addressed here. Most of literature approaches of DFSA focus on two problems, estimation of the number of tags [1]–[7], [11], [12] and frame length adjustment policy [8]–[10], [13], [14].

The simplest and most widely mentioned FbF estimator is proposed by Schoute [1]. The estimated number of tags is 2.39 times the number of collided slots, where 2.39 is the expected number of tags in a collided slot. The authors claimed that this estimator could achieve a system efficiency of 0.426, which is higher than optimal system efficiency of 0.368 under general assumption. However, it is derived under the assumption that the number of tags that transmit in each frame obeys Poisson distribution with unit mean. When the number of tags does not match the frame length, the expected number of tags in a collided slot could be different. An iterative algorithm is proposed in [2] to calculate it so as to improve estimation accuracy. Different from only using the number of collided slots, Chen [3] formulated a posterior probability distribution of the number of tags on the condition of the number of empty, successful and collided slots and suggested setting the estimation as the number when given probability gets maximum. However, he did not consider the dependence of the number of empty, successful and collided slots. An improved version of Chen's algorithm [4] gives the probability of the number of mutually dependent slot types. An estimator is given in closed form formulation. The main disadvantage of these methods is the high computation, which requires specific hardware design on the reader side. An improved linearized combinatorial model (ILCM) [5] is proposed and computation complexity is significantly reduced. Only 10 multiplication operations, two exponential operations and one trigonometric operation are required, which is a constant for one estimation.

To take more chances to adjust the frame length when it is not optimal, a maximum likelihood (ML) estimator is formulated in [7] and further modified towards partly observed frames in a SbS manner. However, details on when to break the frame is not provided. Three certain break points (one-quarter of the frame length, half frame length and three-quarter of the frame length) are investigated and simulated in terms of system efficiency [8]. Results show that breaking frames on one-quarter of them outperforms other breaking points. Furthermore, with extensive simulations, Su *et al.* derived a recommendation setting of breaking points for different frame length [9]. On the other hand, the estimation error with different number of time slots is investigated in [10] and it proximately obeys an exponential distribution along with the slot index in one frame. With this feature that earlier slots always provide more information on the number of tags than latter slots, the authors proposed an early break policy to break current frame when estimation error converges. Most FbF estimators are easy to be modified into SbS ones. However, only observations of one frame are utilized and usually more than one-quarter of the frame are required to obtain a good estimation. Observations in previous frames are not well used.

To take the advantage of observations in previous frames, Multi-frame Maximum-Likelihood (MFML) algorithm is proposed in [6]. In this algorithm, the estimation is obtained based on obervations in all frames. However, it is a FbF estimator and estimation is only obtained when one frame is over. Flôrkemeier [11] proposed a Bayesian estimator and estimation could be obtained in the middle of one frame. Observed evidence in previous frames and finished time slots in current frame are all utilized to enhance estimation accuracy. However, this brings huge computation complexity. Robithoh proposed a modified version of Bayesian method [12]. In this scheme, the probability of the number of tags is updated in a slot-by-slot manner. Bayesian rule is utilized to calculate the posterior probability in each slot. After that, the posterior probability is considered as the prior probability in the next slot. The probability distribution converges as long as slots going on. The system efficiency reaches optimal when the number of tags is large enough. The computation complexity is relatively reduced compared with Flôrkemeier's work. However, it initially sets a fixed range and considers the probability out of the range as zero. The probability will not converge when the number of tags is larger than the upper bound of the fixed range. Besides, the number of multiplication operations required in each slot is related to the number of tags as well.

Recently, physical layer approaches are introduced into RFID systems. In-phase and quadrature information are utilized to recovery signals of multiple tags in one time slot, converting a collided slot into a successful slot. Most researches require multiple antennas receiver [20], specific tag signal strength [21], modified coding mechanisms [22], etc. BiGroup [23] is the first proposal to parallelly decode multiple commodity-off-the-shelf (COTS) tags without any changes to current tags and protocols. Clustering is utilized and SNR higher than 25dB is required to distinguish different transmitting status of multiple tags. These works focus on tag signal recovery issues in physical layer and pay less attention on MAC layer design.

III. CROSS-LAYER DESIGN

A. SYSTEM MODEL AND CLAA

In this paper, we consider slotted ALOHA-based system as a special DFSA system in which every frame is early stopped after the first slot. Frame length in DFSA is used to represent access probability in slotted ALOHA-based system. In other words, every slot is an early stopped frame and access probability is decided by the frame length. Each frame includes only one implemented slot (the first slot) and multiple virtual slots (the remaining slots). Apparently, only the tags choosing the first slot (implemented slot) have the chance to transmit their signals and the remaining slots (virtual slots) are discarded. Access probability as well as frame length is updated in a slot by slot manner. An example is given in Fig.1. In the first frame, frame length is set to 8 and more than 2 tags is transmitting in the first slot, making it a collided slot. After that, the remaining seven slots are virtual slots which are not implemented, and a new frame is started with length of 16. In this frame, the first slot is empty, and remaining fifteen slots are virtual slots. The following frames run in the same way. To maximize system efficiency, the reader updates frame length as well as access probability every slot based on the estimated number of tags. Frame length could be any natural number. This algorithm complies with EPCglobal Class-1 Generation-2 protocol (short as EPC G2 in the following paper) when the frame length is limited to 2, 4, 8, etc.

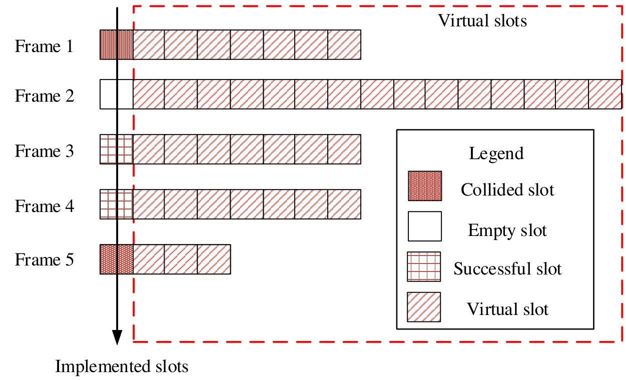

FIGURE 1. System model of slotted ALOHA-based system.

Bayesian inference is a widely used method of statistical inference in the dynamic analysis of a sequence of data, which is a good SbS estimator for RFID systems. Bayesian inference could be expressed in briefly that the posterior is proportional to likelihood times the prior. Likelihood indicates the probability of the observed data on the condition of given parameter value. The prior indicates the probability of given parameter(s) before any data is observed and the posterior indicates the probability of the parameter(s) after taking into account the observed data. Bayesian inference is executed with a sequence of observed data. The posterior probability considering one observed data is set to the prior probability in the next round.

In this work, the number of tags transmitting in current slot is considered as the observed data while the number of tags to be identified in the read range is considered as a parameter. The prior probability is denoted as $P(N)$. N denotes the number of tags to be identified, which is distributed from zero to infinite. In each slot, tags access the channel with the probability of p. The likelihood function is expressed in (1), which follows Binomial distribution. F denotes the number of tags in current slot.

$$P(F|N) = \binom{F}{N} p^F (1-p)^{N-F} \tag{1}$$

The posterior probability is determined by Bayes' rule, as shown in (2).

$$P(N|F) = \frac{P(N)P(F|N)}{P(F)} \propto P(N)P(F|N) \tag{2}$$

According to Bernstein-von Mises theorem, with independent and identically distributed trials, the posterior probability will converge to a Gaussian distribution, which could be utilized to estimate the number of tags to be identified. As shown in (3), the estimated number of tags is set to the expectation of the posterior.

$$\hat{n} = \sum_N NP(N|F) \tag{3}$$

Though Bayesian inference provides a promising performance on estimation accuracy, some revisions are required to match UHF RFID systems. First of all, dealing with probability distributed from zero to infinite is not efficient in practice.

Algorithm 1 Cross Layer Anti-Collision Algorithm (CLAA)

Input : L_{init}
output : $\{ID_{tag}\}$
global : $L = L_{init}$; $F = 0$; $\mu = \sigma = N_{\max} = L_{init}/2$;
$Q = \log_2(L)$; *Query*(Q);
while *not* ($F == 0$ *and* $Q == 0$) **do**
$F = PEAC()$;
if ($F == 1$) **then**
update $\{ID_{tags}\}$;
end if
$\hat{n} = MEAMB(F, \mu, \sigma)$;
$Q' = optQ(\hat{n})$;
if $(Q' == Q)$ **then** *QueryRep* () ;
else *QueryAdjust* () ;
end if
end while

The distribution range of the posterior is set to zero to a fixed maximum number N_{max} and uniform distributed prior is assumed in [12]. However, this could result in unknown error when the initial number of tags is larger than N_{max}. In this work, a dynamic distribution range adjustment mechanism is introduced. The distribution range is doubled when the posterior is centered at the top of it. Similar, N_{max} is reduced by half when the posterior is centered at the bottom.

Secondly, the reader needs to record all values of the posterior probability and update them with likelihood and observed data. The minimum number of multiplication operations required in each slot is $2N_{max}$, which is related to the number of tags. In this work, a MAC layer estimation algorithm based on Bayesian inference (MEAMB) is introduced, in which Gaussian function is used to approximate the posterior curve. Only two key factors are updated, and complexity is significantly reduced. Details are provided in Section III.B.

Furthermore, accurate number of tags in current slot (F) is not available in the reader side. Usually, slots are divided into three types, empty ($F = 0$), successful ($F = 1$) and collided ($F > 1$). Without ability of distinguishing slots with more than one tag, these conditions are grouped as one condition (collided). In other words, likelihood functions when there are more than one tag are considered as the same. This would reduce convergence speed and estimation accuracy. For better estimation accuracy and faster convergence, slots need to be divided into more categories. An physical layer estimation algorithm based on clustering (PEAC) is proposed to divide slots into five categories, empty ($F = 0$), successful ($F = 1$) and two tags collided ($F = 2$), three tags collided ($F = 3$) and other collided ($F > 3$). The detailed design is provided in Section III.C.

The proposed CLAA is shown as Algorithm.1. Here we assume the system complies with EPC G2 protocol. At first, the reader sets the initial frame length as L_{init} and broadcast it through Query command. In each time slot, tags respond based on the frame length L. After that, slot type (F) is determined with PEAC (shown as Algorithm.3), and the number of tags ($\hat{n}$) is estimated with MEAMB (shown as Algorithm.2). Optimal frame length is decided by the estimated number of tags [8]. When it is the same as current frame length, the reader send QueryRep command to carry on current frame. Otherwise, the reader send QueryAdjust command to adjust the frame length. Frame length could be updated after every time slot. The process is repeated until the frame length is set to one and no tags response. $N_{\max}$, μ and σ are global variables stored in public storage and used in MEAMB.

B. MAC LAYER ESTIMATION ALGORITHM BASED ON MODIFIED BAYESIAN INFERENCE (MEAMB)

In this sub-section, we propose a MAC layer estimation algorithm based on modified Bayesian inference (MEMAB) using Gaussian function to approximate the posterior probability for complexity reduction. It is well known that Gaussian function is uniquely determined by two number, expectation and standard deviation. Instead of dealing with all values of the posterior probability curve, only two factors and the distribution range are required to represent it. The prior probability is set to Gaussian distribution and likelihood function is approximated to keep the posterior curve a Gaussian function. It is worth noting that Gaussian function is used to approximate the probability curve within the distribution range. It does not mean that the probability of the number of tags obeys Gaussian distribution. The probability in the distribution range is normalized to make it sum to one in each slot, especially when the distribution range is updated. Estimation of the number of tags is calculated based on expectation, standard deviation and the distribution range. Expectation and standard deviation in current slot are denoted as μ_c and σ_c while those in next slot are denoted as μ_n and σ_n. Upper bound of the distributed range is denoted as N_{max}.

For empty slot, likelihood function is an exponential function of the number of tags. The posterior probability is calculated as (4).

$$\begin{aligned} P(N|F=0) &= \frac{P(N)\,P(F=0|N)}{P(F=0)} = \frac{exp\left(\frac{-(N-\mu_c)^2}{2\sigma_c{}^2}\right)(1-p)^N}{\sqrt{2\pi}\sigma_c P(F=0)} \\ &= \frac{exp\left(-\mu_c{}^2 + \left[\mu_c + \sigma_c{}^2 ln(1-p)\right]^2\right)}{\sqrt{2\pi}\sigma_c P(F=0)} \\ &\quad \times exp\left\{\frac{-\left[N-\mu_c-\sigma_c{}^2 ln(1-p)\right]^2}{2\sigma_c{}^2}\right\} \end{aligned} \tag{4}$$

Apparently, the posterior probability is still a Gaussian function with different expectation and the same standard deviation. Approximation is not required in this case. As shown in (5), expectation in the next slot is updated by current expectation and standard deviation.

$$\mu_n \approx \mu_c - \sigma_c{}^2 p \tag{5}$$

where $-\ln(1-p) \approx 1/p$ when p is small enough.

For slots with known F, likelihood function is an inverted U curve. In these conditions, Gaussian function is a good approximator. We consider original likelihood function as a probability function and normalize it to sum to one. After that, expectation and standard deviation of approximated Gaussian function are set to those of normalized likelihood.

For successful slot, expectation and standard deviation of normalized likelihood is calculated as (6) and (7).

$$
\begin{aligned}
&E(F=1|N)\\
&=\sum_{N=0}^{+\infty} N\left[P(F=1|N)\Big/\sum_{N=0}^{+\infty} P(F=1|N)\right]\\
&=\sum_{N=0}^{+\infty} NP(F=1|N)\Big/\sum_{N=0}^{+\infty} P(F=1|N)\\
&=\sum_{N=0}^{+\infty} N^2p(1-p)^{N-1}\Big/\sum_{N=0}^{+\infty} Np(1-p)^{N-1}=2/p-1\\
&D(F=1|N)\\
&=E\left(F=1|N^2\right)-[E(F=1|N)]^2 \qquad (6)\\
&=\sum_{N=0}^{+\infty} N^2\left[P(F=1|N)\Big/\sum_{N=0}^{+\infty} P(F=1|N)\right]-[2p-1]^2\\
&=\sum_{N=0}^{+\infty} N^3p(1-p)^{N-1}\Big/\sum_{N=0}^{+\infty} Np(1-p)^{N-1}-[2p-1]^2\\
&=2/p^2-2/p \qquad (7)
\end{aligned}
$$

As mentioned in Section III.A, accurate number of tags F is not available. For most UHF RFID systems, conditions when the number of tags is larger than one is grouped and likelihood function is a log-like curve. This could bring more deviation to approximate it with a Gaussian function compared with known F cases. When the number of tags matches the number of slots, collision happens with a probability of 0.264, which cannot be ignored. To recover this problem, slot types are further divided into 5 categories. When the number of tags is lower than three, likelihood is an inverted U curve with known F and approximated with a Gaussian function. Only the likelihood function of slot type in which the number of tags is larger than three is a log-like curve. It happens with a much lower probability of 0.0187. Expectation and standard deviation is set to a large number based on the distribution range. As shown in (8) and (9), μ_F and σ_F denote expectation and standard deviation of approximated Gaussian function, respectively.

$$
\mu_F=\begin{cases}(F+1)/p-1, & 1\le F\le 3\\ N_{max}/p, & F>3\end{cases} \qquad (8)
$$

$$
\sigma_F=\begin{cases}\sqrt{(F+1)/p^2-(F+1)/p}, & 1\le F\le 3\\ \sqrt{N_{max}/p^2}, & F>3\end{cases} \qquad (9)
$$

Similar with empty slot, the updated probability is still a Gaussian function with different expectation and different standard deviation. As shown in (10), the posterior probability distribution when $F>0$ is calculated by Bayesian rule.

$$
\begin{aligned}
P(N|F)&\propto P(N)P(F|N)\approx\frac{exp\left(\frac{-(N-\mu_c)^2}{2\sigma_c{}^2}+\frac{-(N-\mu_F)^2}{2\sigma_F^2}\right)}{2\pi\sigma_c\sigma_F}\\
&=\alpha exp\left(-\frac{\left(N-\frac{\sigma_c{}^2\mu_F+\sigma_F^2\mu_c}{\sigma_F^2+\sigma_c{}^2}\right)^2}{2\sigma_c{}^2\sigma_F^2/(\sigma_F^2+\sigma_c{}^2)}\right)\\
\alpha&=\frac{exp\left(-\frac{\mu^2\sigma_F^2+\mu_F^2\sigma_c{}^2-\left(\frac{\sigma_c{}^2\mu_F+\sigma_F^2\mu_c}{\sigma_F^2+\sigma_c{}^2}\right)^2}{2\sigma_c{}^2\sigma_F^2/(\sigma_F^2+\sigma_c{}^2)}\right)}{2\pi\sigma_c\sigma_F P(F)}
\end{aligned} \qquad (10)
$$

For successful slot, the number of tags unidentified is reduced by one. As a result, expectation of the probability is reduced by one. Finally update of the posterior probability is reduced to that of these two key parameters, shown as (11) and (12).

$$
\mu_n=\begin{cases}\mu_c-\sigma_{old}{}^2/p, & F=0\\ \dfrac{\sigma_c{}^2\mu_F+\sigma_F^2\mu_c}{\sigma_F^2+\sigma_c{}^2}-1, & F=1\\ \dfrac{\sigma_c{}^2\mu_F+\sigma_F^2\mu_c}{\sigma_F^2+\sigma_c{}^2}, & F>1\end{cases} \qquad (11)
$$

$$
\sigma_n=\begin{cases}\sigma_c, & F=0\\ \sqrt{\dfrac{\sigma_c{}^2\sigma_F^2}{\sigma_F^2+\sigma_c{}^2}}, & F>0\end{cases} \qquad (12)
$$

As mentioned previously, the estimated number of tags is calculated based on expectation, standard deviation and the distribution range. The probability is normalized, and expectation is calculated within the distribution range. Result is shown in (13).

$$
\begin{aligned}
\hat{n}&=\sum_{N=0}^{N_{max}}\left[NP(N)\Big/\sum_{N=0}^{N_{max}}P(N)\right]\\
&=\frac{\sum_{N=0}^{N_{max}}NP(N)}{\sum_{N=0}^{N_{max}}P(N)}\approx\frac{\int_0^{N_{max}}NP(N)}{\int_0^{N_{max}}P(N)}\\
&=\frac{\int_0^{N_{max}}\frac{x}{\sqrt{2\pi}\sigma_c}exp\left(\frac{-(x-\mu_c)^2}{2\sigma_c{}^2}\right)dx}{\int_0^{N_{max}}\frac{1}{\sqrt{2\pi}\sigma_c}exp\left(\frac{-(x-\mu_c)^2}{2\sigma_c{}^2}\right)dx}\\
&=\mu_c+\frac{\frac{2\sigma_c}{\sqrt{2\pi}}\left[exp\left(\frac{-(-\mu_c)^2}{2\sigma_c{}^2}\right)-exp\left(\frac{-(N_{max}-\mu_c)^2}{2\sigma_c{}^2}\right)\right]}{erf\left(\frac{\mu_c}{\sigma_c\sqrt{2}}\right)+erf\left(\frac{(N_{max}-\mu_c)}{\sigma_c\sqrt{2}}\right)}
\end{aligned} \qquad (13)
$$

Algorithm 2 MAC Layer Estimation Algorithm Based on Modified Bayesian Inference (MEAMB)

$Input : F$
$output : \hat{n}$
$global : L; \mu; \sigma; N_{\max};$
$update\ \mu\ and\ \sigma\ with\ (8), (9), (11)\ and\ (12);$
if $\left(\mu_c + 2\sigma_c > 4N_{max}/5\right)$ **then**
$N_{\max} = 2N_{\max};$
elseif $\left(\mu_c - 2\sigma_c < N_{max}/5\right)$ **then**
$N_{\max} = N_{\max}/2;$
end if
$calculate\ \hat{n}\ with\ (13);$

Algorithm 3 Physical Layer Estimation Algorithm Based on Clustering (PEAC)

$Input : s(t)$
$output : F$
if $\left(\sum [s(t)]^2 \le P_{min}\right)$ **then**
$F = 0;$
else
$\{\langle x_i, y_i\rangle \mid i = 1, 2, 3\ldots\} = meanshift\,[s(t)];$
$N_{clu} = clusterAdj\,(\{\langle x_i, y_i\rangle \mid i = 1, 2, 3\ldots\});$
$F = floor\left[\log 2\,(N_{clu})\right];$
end if

where $erf(*)$ denotes Gaussian error function and its approximation is shown as (14) [26].

$$erf(x) \approx 1-\left(a_1 t + a_2 t^2 + a_3 t^3\right) e^{-x^2}, \quad t = \frac{1}{1+px} \tag{14}$$

where a_1, a_2, a_3 and p are all constant number.

Finally, MEMAB is shown as Algorithm 2. In each slot, expectation (μ) and standard deviation (σ) is updated based on observed slot type (F) with previous expectation and standard deviation. The distribution range (N_{max}) is updated if the probability distribution meet specific condition. The estimated number of tags ($\hat{n}$) is calculated with (13). Only (8), (9), (11), (12) and (13) are computed in each time slot, which includes 38 multiplication operations and 2 exponential operations and does not rely on the number of tags.

C. PHYSICAL LAYER ESTIMATION ALGORITHM BASED ON CLUSTERING (PEAC)

In this sub-section, we propose a physical layer estimation algorithm based on clustering (PEAC) to extend the number of slot types to 5. We consider a typical scenario with one RFID reader and multiple COTS tags. Tags acquire power from continuous wave transmitted by the reader. Backscatter modulation is used to transmit signals to the reader when appropriate command is received. Signals are down-converted to baseband on the reader side. The reader is required to estimate the number of tags based on these signals. As shown in (15), baseband signals in receive path consist of three components, backscatter signal of tags, self-jammer and noise.

$$s(t) = \sum_{i=1}^{n} A_i e^{-j\theta_i - j\varphi(t)} + \eta e^{-j\theta_0 - j\varphi(t)} + \phi(t) \tag{15}$$

The first component indicates the signals of multiple tags. The second one indicates the signals of self-jammer caused by imperfect isolation between transmission and reception paths. The last one represents additive white Gaussian noise (AWGN). The index of collided tags in one time slot is denoted as i while transmitted data and the initial phase of the i-th tag is denoted as A_i and θ_i. The amplitude and phase of self-jammer is denoted as θ_0 and η. AWGN and time-varying phase noise in the receiver is denoted as $\phi(t)$ and $\varphi(t)$, respectively. Some properties are obtained from (15).

1) If we plot received signal samples in a 2-dimension coordinates, in-phase amplitude as x axis and quadrature amplitude as y axis, they gather around several points, form as clusters. The number of clusters is decided by the number of tags. Every tag has two transmission status, the size of full status space is 2^F , where F denotes the number of tags.
2) The clusters are always located in pairs, symmetry to the center of all samples. For every cluster, reverse all the tag status, a symmetric cluster is obtained. Their symmetric center is located at the center of all samples. The coordinates of the center point is located at the mean of coordinates of all samples.

A straight forward way to find the number of tags is to divide signal samples into clusters with a clustering algorithm. After obtaining the number of clusters, the number of tags is decided. Proposed PEAC operates as Algorithm.3. Firstly, energy detection is utilized to detect an empty slot, where P_{min} denotes the power threshold. If it is empty, the algorithm stops and return empty. If it is not, mean shift algorithm (shown as Algorithm.4) is carried out to make initial cluster decision, where x_i and y_i denote in-phase axis and quadrature axis coordinate of i-th cluster center. After that, a cluster adjustment scheme (shown as Algorithm.5) is carried out to discard isolated noise clusters and provide final number of clusters N_{clu}, which is used to determine the number of tags F.

Mean shift algorithm is a widely used clustering algorithm for locating the maxima-the modes-of a density function (kernel function) given discrete data sampled from that function. Cluster centers are updated iteratively towards the direction of the maximum increase in the density when Gaussian kernel is utilized. It is easy to implemented in FPGA or ASIC with corresponding modifications [27]. Algorithm.4 shows the basic format of it. At first, several random cluster centers are initialized. Coordinates of the i-th center is denoted as a complex number $c(i)$. For each cluster, weighted mean is calculated based on coordinates of neighborhood samples, where $m(i)$ and $\aleph(i)$ denote the weighted mean and collection of neighbors of i-th cluster, respectively. Cluster centers are

Algorithm 4 Mean Shift Algorithm (Meanshift)

Input : $s(t)$
output : $\{c(i) = x_i + jy_i | i = 1, 2, 3..., 20\}$
for
$i = 1 : 20$
$m(i) = rand(); \quad c(i) = 0;$
end for
while $\left(\sum_{i=1}^{20} \|c(i) - m(i)\|^2 \; != 0 \right)$ **do**
for $i = 1 : 20$
$c(i) = m(i);$
$\aleph(i) = getNeighbors\,[c(i), s(t)];$
$m(i) = \frac{\sum_{s(t_x)\in\aleph(i)} K[s(t_x) - c(i)]s(t_x)}{\sum_{s(t_x)\in\aleph(i)} K[s(t_x) - c(i)]};$
end for
end while
return $unique\,[\{c(i)\}];$

Algorithm 5 Cluster Adjustment (clusterAdj)

Input : $\{c(i) = x_i + jy_i | i = 1, 2, 3..., 20\}; s(t); \aleph(i)$
output : N_{clu}
$c_0 = \sum s(t) / length(s(t)); \; N_{clu} = 0;$
for $i = 1 : 20$
for $j = 1 : 20$
$\varphi(i, j) = \left\| \frac{c(i)+c(j)}{2} - c_0 \right\|^2;$
end for
end for
for $i = 1 : 20$
$(\varphi_{\min}, index) = minimum\,[\varphi(i, :)];$
if $length\,[\aleph(i)] - length\,[\aleph(index)] < \delta$ **then**
$N_{clu} = N_{clu} + 1;$
end if
end for
return N_{clu};

shifted based on the weighted mean until convergence. Final number of clusters is usually less than the number of initial clusters because some clusters merge at the same center. The number of initial clusters is set to 20 to make sure that condition of 3 tags (8 clusters) is detectable. Formal format of Gaussian kernel function is shown as (16).

$$K(x) = e^{-\frac{x}{2\sigma_x^2}} \tag{16}$$

Algorithm.5 shows the details of cluster adjustment algorithm, in which isolated noise clusters are discarded. As mentioned above, clusters are distributed in pairs and every cluster have a symmetrical one with similar number of samples. In this algorithm, a symmetric indicator is defined to evaluate the symmetric level between two clusters, where $\varphi(i, j)$ denotes the indicator of i-th and j-th clusters. For each cluster, the most symmetric one is found according to its minimum symmetric indicator. After that, the difference between the number of samples in both cluster is checked. If it is within a threshold δ, both clusters are considered as validate. Otherwise, it is discarded. The threshold is set to half of the number of samples in one transmitting status.

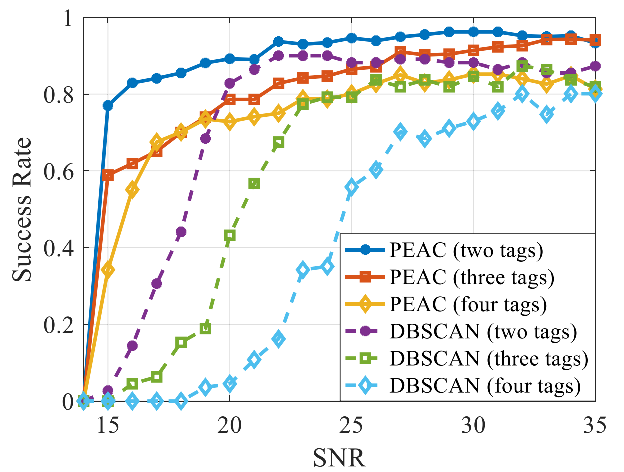

FIGURE 2. Success rate of PEAC and DBSCAN.

IV. PERFORMANCE EVALUATION

A. PERFORMANCE OF PEAC

The performance of PEAC is evaluated in terms of accuracy or success rate, which is defined as the number of successful experiments over the total number of experiments. Another clustering algorithm Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is simulated in the same parameters to be compared with. In order to improve the reliability of results, simulations are carried out 10000 times in each parameter group of SNR and the number of tags. In each experiment, pseudo tag signals are generated based on (15). Signal strength and the initial phase of tags are randomly selected. Both algorithms are used to determine the number of tags. The real number of tags and determined number of tags are both recorded. As shown in (17), $p(\hat{n}|n)$ denotes the probability of determined number of tags on the condition of real number of tags, where $N_{real}(n)$ denotes the number of experiments when the real number is n and $N_{determined}(\hat{n})$ denotes the number of experiments when the real number is n and determined as $\hat{n}$. Apparently, success rate when the number of tags is n equals to the probability of $p(n|n)$.

$$p(\hat{n}|n) = \frac{N_{determined}(\hat{n})}{N_{real}(n)} \tag{17}$$

Fig.2 shows success rate of PEAC and DBSCAN in different conditions of SNR and the number of tags. Success rate of proposed PEAC is higher than DBSCAN in all conditions. When SNR is larger than 18dB, success rate of proposed PEAC is larger than 0.9 when the real number of tags is 2 or 3. Success rate is relatively lower when there are 4 tags, still over 0.8 when SNR is large enough. Conditions when the number of tags is larger than 4 is not evaluated here due to its low happening probability.

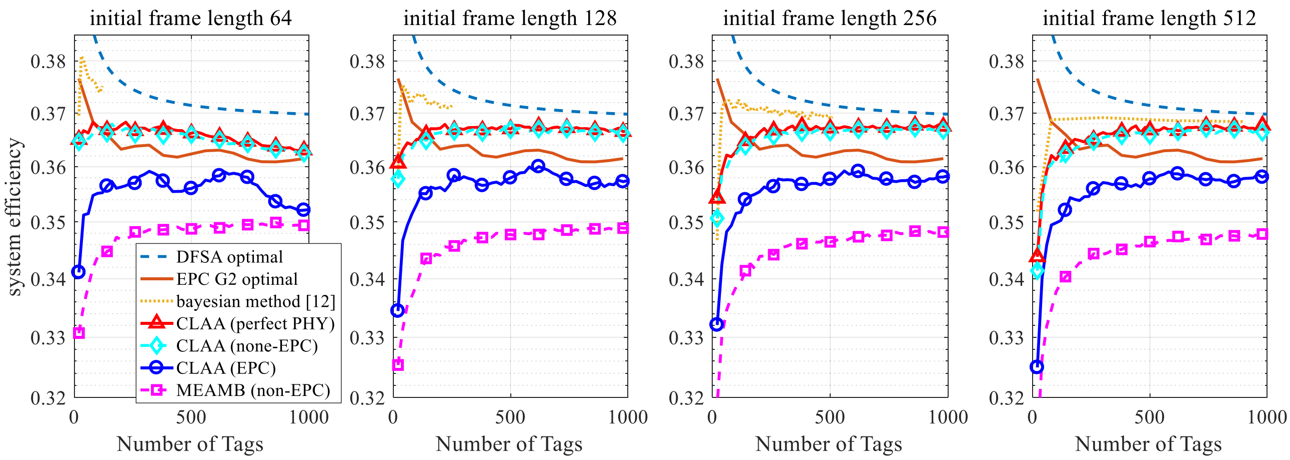

FIGURE 3. Performance comparison between CLAA and its variants.

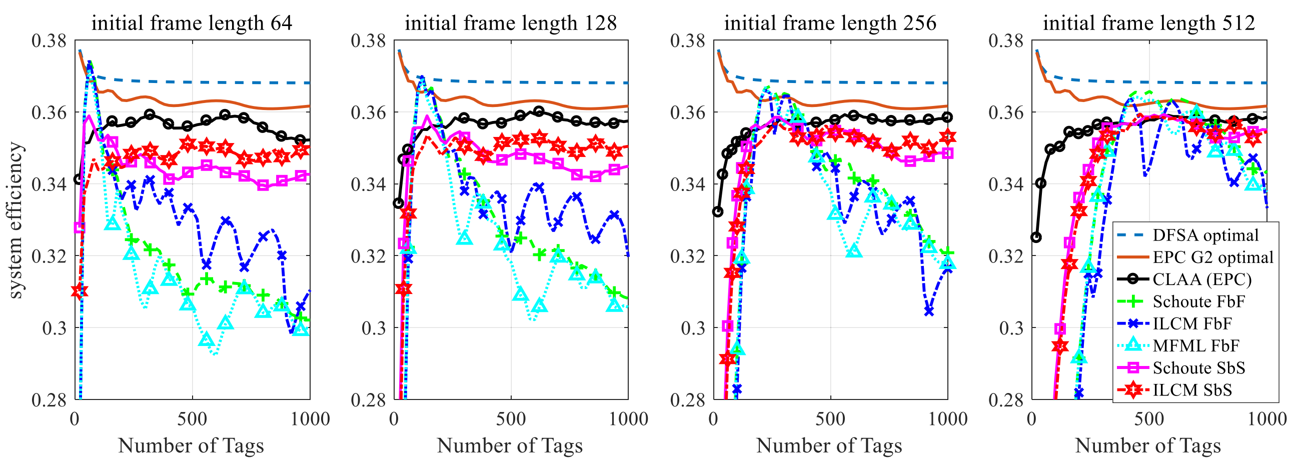

FIGURE 4. Performance comparison between CLAA (EPC) and state-of-the-art algorithms.

B. PERFORMANCE OF CLAA

CLAA and its variants have been evaluated with Monte Carlo method. Three low complexity FbF estimators and corresponding modified SbS estimators are simulated for comparison. Table 1 gives a brief of the compared algorithms. All algorithms are simulated under multiple parameter groups of initial frame length and the number of tags to be identified. For reliability, 2000 experiments are carried out for each parameter group and results are averaged.

As shown in Fig.3, CLAA and its variants are compared with Bayesian method [12]. Bayesian method [12] performs the best because of its high accuracy of estimation. However, it is not available when the number of tags is larger than the initial distribution range N_{max}, and the system efficiency is considered as zero. Other algorithms perform more independent on the initial frame length. MEAMB (non-EPC) performs the worst with a loss of about 2% compared with Bayesian method, which is mainly caused by Gaussian approximation. CLAA (non-EPC) performs much better than MEAMB (non-EPC) and close to Bayesian method in large number scenarios, thanks to PEAC employed in physical layer. CLAA (perfect PHY) performs almost the same as CLAA (non-EPC) in all conditions. This indicates that the proposed PEAC algorithm performs well enough. CLAA (EPC) performs about 1% worse than CLAA (non-EPC) due to limitation of frame length.

Fig.4 shows the comparison between CLAA (EPC) and other state-of-the-art algorithms. CLAA (EPC) outperforms others in most conditions. FbF based algorithms are slightly better than CLAA (EPC) exceeding EPC G2 optimal when the initial number of tags is near the initial frame length. However, they perform much worse in other conditions. This is because the employed estimation algorithms perform better when the frame length is close to the number of tags than otherwise and less slots are wasted when the initial frame length matches the initial number of tags. On the contrary, SbS algorithms perform more stable and independent on the initial frame length. However, they perform worse when the number of tags is small, especially when the initial frame

TABLE 1. Simulated algorithms.

Algorithm	Algorithm details
Bayesian method [12]	The prior probability is set to uniform distribution. The distribution range is initially fixed. Only three slot types are distinguished in physical layer.
CLAA (perfect PHY)	A perfect physical layer algorithm is employed and the number of tags in single time slot is assumed known in MAC layer.
CLAA (non-EPC)	Same as described in Section III. Frame length is set to the estimated number of tags. PEAC makes mistakes with probabilities evaluated in section IV.A.
MEAMB (non-EPC)	PEAC is not employed and only three slot types are distinguished in physical layer.
CLAA (EPC)	Same as described in Section III. Frame length is limited to power of 2 and chosen based on optimal frame length described in [8]. PEAC makes mistakes with probabilities evaluated in section IV.A.
Schoute FbF	Schoute algorithm is used to estimate number of tags and the frame length is updated frame by frame.
MFML FbF	Q value is updated frame by frame. Multi-frame maximum likelihood algorithm is used to estimate number of tags.
ILCM FbF	ILCM algorithm is used to estimate number of tags and the frame length is updated frame by frame.
Schoute $L/4$	Check if Q value needs to be updated when slot index is exactly L/4. Schoute algorithm is modified in SbS manner and used to estimate number of tags.
ILCM $L/4$	Check if Q value needs to be updated when slot index is exactly L/4. ILCM is modified in SbS manner and used to estimate number of tags.
Schoute SbS	Check if Q value needs to be updated when slot index is larger than L/4. Schoute algorithm is modified in SbS manner and used to estimate number of tags.
ILCM SbS	Check if Q value needs to be updated when slot index is larger than L/4. ILCM is modified in SbS manner and used to estimate number of tags.

TABLE 2. Mean and variances of system efficiency.

	Efficiency Expectation (%)				Efficiency Variances (%)			
Algorithm \ L_{init}	64	128	256	512	64	128	256	512
Bayesian method [12]	4.51	9.29	18.85	36.58	150.7	261.8	345.2	0.9263
CLAA (perfect PHY)	36.57	36.67	36.63	36.55	0.0233	0.0161	0.0599	0.1531
CLAA (non-EPC)	36.51	36.61	36.56	36.48	0.0234	0.0252	0.0788	0.1763
MEAMB (non-EPC)	34.76	34.60	34.49	34.40	0.1402	0.2239	0.2847	0.3926
CLAA (EPC)	35.57	35.64	35.60	35.55	0.0943	0.1575	0.2097	0.3202
Schoute FbF	31.91	32.52	32.88	31.85	3.931	10.49	27.70	62.71
ILCM FbF	32.90	33.20	32.43	31.15	3.462	10.02	28.09	62.47
MFML FbF	31.33	31.98	32.42	31.66	3.986	10.25	26.68	61.16
Schoute $L/4$	34.04	34.16	34.07	33.35	0.2389	1.702	7.402	21.01
ILCM $L/4$	34.01	34.00	33.71	32.95	0.7577	2.697	8.694	21.95
Schoute SbS	34.45	34.59	34.49	33.76	0.2711	1.742	7.597	21.70
ILCM SbS	34.70	34.72	34.41	33.63	0.3474	2.225	8.647	23.01

length is large. This is because a minimum number of time slots are required in each frame to obtain good estimation of the number of tags. CLAA (EPC) performs the best because it takes all time slots into considerations. Efficiency increases rapidly with the number of tags and approaches 0.356 when the number of tags reaches to 200.

For better comparison between the proposed CLAA and the state-of-the-art algorithms, mean and variance of the system efficiency is evaluated. Here we assume that the number of tags are uniform distributed random number ranging from 0 to 1000. For a specific initial frame length, μ_L and δ_L denote the mean and variance of system efficiency, which could be calculated by (18) and (19), where $\gamma_L(n)$ denotes average system efficiency under initial frame length of L and the number of tags of n. Table 2 shows comparison between these algorithms. CLAA (non-EPC) achieves an average system efficiency of 36.67% and variance of 0.016 while CLAA (EPC) achieves an average system efficiency of 35.64% and variance of 0.157 on the condition of initial frame length as 128. This is very close to DFSA optimal (36.8%) and EPC G2 optimal (36%) in large number conditions. ILCM SbS performs the best among compared DFSA algorithms, obtaining system efficiency of 34.70% and variance of 0.347 when the initial frame length is set to 64, both worse than CLAA (EPC).

$$\mu_L = \frac{\sum\limits_{n=\{20:20:1000\}} \gamma_L(n)}{50} \tag{18}$$

$$\delta_L = \frac{\sum\limits_{n=\{20:20:1000\}} \left[\gamma_L(n) - \mu_L\right]^2}{49} \tag{19}$$

V. CONCLUSION

This paper proposed a novel cross layer anti-collision algorithm for slotted ALOHA-based UHF RFID systems. The proposed CLAA achieves the averaged system efficiency of 35.64% on the condition of EPC and 36.67% for non-EPC systems when the number of tags has an uniform distribution from 0 to 1000. The proposed method outperforms the state-of-the-art ones in terms of system efficiency and stability. It is independent on the number of tags and the initial frame length thanks to its slot-by-slot nature. Furthermore, the proposed algorithm makes a good balance between performance and computation cost. The computational cost in MAC layer is reduced to 38 multiplication operations and 2 exponential operations at the price of an additional computation part in physical layer where the computation resource is sufficient and the calculation in hardware is more stable with less time delay. Future investigations will focus on hardware implementation of PEAC and applications of MEAMB in other slotted communication systems.

REFERENCES

[1] F. Schoute, "Dynamic frame length ALOHA," *IEEE Trans. Commun.*, vol. 31, no. 4, pp. 565–568, Apr. 1983.

[2] J. B. Eom and T. J. Lee, "Accurate tag estimation for dynamic framed-slotted ALOHA in RFID systems," *IEEE Commun. Lett.*, vol. 14, no. 1, pp. 60–62, Jan. 2010.

[3] W.-T. Chen, "An accurate tag estimate method for improving the performance of an RFID anticollision algorithm based on dynamic frame length ALOHA," *IEEE Trans. Autom. Sci. Eng.*, vol. 6, no. 1, pp. 9–15, Jan. 2009.

[4] E. Vahedi, V. W. S. Wong, I. F. Blake, and R. K. Ward, "Probabilistic Analysis and Correction of Chen's Tag Estimate Method," *IEEE Trans. Autom. Sci. Eng.*, vol. 8, no. 3, pp. 659–663, Jul. 2011.

[5] P. Šolić et al., "Improved linearized combinatorial model (ILCM) for optimal frame size selection in ALOHA-based RFID systems," in *Proc. IEEE Int. Conf. Commun. Workshops (ICC)*, Budapest, Hungary, Jun. 2013, pp. 1072–1077.
[6] J. Vales-Alonso, V. Bueno-Delgado, E. Egea-Lopez, F. J. Gonzalez-Castaño, and J. Alcaraz, "Multiframe maximum-likelihood tag estimation for RFID anticollision protocols," *IEEE Trans. Ind. Informat.*, vol. 7, no. 3, pp. 487–496, Aug. 2011.
[7] B. Knerr, M. Holzer, C. Angerer, and M. Rupp, "Slot-wise maximum likelihood estimation of the tag population size in FSA protocols," *IEEE Trans. Commun.*, vol. 58, no. 2, pp. 578–585, Feb. 2010.
[8] W. T. Chen, "A fast anticollision algorithm for the EPCglobal UHF class-1 generation-2 RFID standard," in *IEEE Commun. Lett.*, vol. 18, no. 9, pp. 1519–1522, Sep. 2014.
[9] J. Su, Z. Sheng, D. Hong, and G. Wen, "An effective frame breaking policy for dynamic framed slotted ALOHA in RFID," *IEEE Commun. Lett.*, vol. 20, no. 4, pp. 692–695, Apr. 2016.
[10] P. Šolić, J. Radić, and N. Rožić, "Early frame break policy for ALOHA-based RFID systems," *IEEE Trans. Autom. Sci. Eng.*, vol. 13, no. 2, pp. 876–881, Apr. 2016.
[11] C. Floerkemeier, "Bayesian transmission strategy for framed ALOHA based RFID protocols," in *Proc. IEEE Int. Conf. RFID*, Grapevine, TX, USA, Mar. 2007, pp. 228–235.
[12] R. Annur, W. Srichavengsup, S. Nakpeerayuth, and L. Wuttitsittikulkij, "Bayesian method of slotted aloha based anti-collision protocol for RFID systems," in *Proc. IEEE 12th Int. Symp. Auto. Decentralized Syst.*, Taichung, Taiwan, Mar. 2015, pp. 87–90.
[13] W. Chen, "Optimal frame length analysis and an efficient anti-collision algorithm with early adjustment of frame length for RFID systems," *IEEE Trans. Veh. Technol.*, vol. 65, no. 5, pp. 3342–3348, May 2016.
[14] J. Su, X. Zhao, D. Hong, Z. Luo, and H. Chen, "Q-value fine-grained adjustment based RFID anti-collision algorithm,"Âİ *IEICE Trans. Commun.*, vol. 99, no. 7, pp. 1593–1598, Jun. 2016.
[15] J. Su, L. Xie, Y. Yang, Y. Han, and G. Wen, "A collision arbitration protocol based on specific selection function," *Chin. J. Electron.*, vol. 26, no. 4, pp. 864–870, 2017.
[16] J. Su, Y. Chen, Z. Sheng, and L. Sun, "Bit query based M-ary tree protocol for RFID tags identification," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Singapore, Dec. 2017, pp. 1–7.
[17] J. Su, G. Wen, and D. Hong, "A new RFID anti-collision algorithm based on the Q-ary search scheme," *Chin. J. Electron.*, vol. 24, no. 4, pp. 679–683, 2015.
[18] Y. Cui and Y. Zhao, "Performance evaluation of a multi-branch tree algorithm in RFID," *IEEE Trans. Commun.*, vol. 58, no. 5, pp. 1356–1364, May 2010.
[19] J. Su, Z. Sheng, L. Xie, G. Li, and A. X. Liu, "Fast splitting based tag identification algorithm for anti-collision in UHF RFID system," *IEEE Trans. Commun.*, vol. 67, no. 3, pp. 2527–2538, 2019. doi: 10.1109/TTHZ.2016.2544142.
[20] C. Angerer, R. Langwieser, and M. Rupp, "RFID reader receivers for physical layer collision recovery," *IEEE Trans. Commun.*, vol. 58, no. 12, pp. 3526–3537, Dec. 2010.
[21] K. Fyhn, R. Jacobsen, P. Popovski, A. Scaglione, and T. Larsen, "Multipacket reception of passive UHF RFID tags: A communication theoretic approach," *IEEE Trans. Signal Process.*, vol. 59, no. 9, pp. 4225–4237, Sep. 2011.
[22] A. N. Parks, A. Liu, S. Gollakota, and J. R. Smith, "Turbocharging ambient backscatter communication,"Âİ in *Proc. ACM SIGCOMM*, Chicago, IL, USA, 2014, pp. 619–630.
[23] J. Ou, M. Li, and Y. Zheng, "Come and be served: Parallel decoding for COTS RFID tags," *IEEE/ACM Trans. Netw.*, vol. 25, no. 3, pp. 1569–1581, Jun. 2017.
[24] Y. Zeng, H. Wu, K. Yang, and X. Wang, "Dynamic-scale transformation for UHF RFID tag collision separation on physical layer," in *Proc. 4th Int. Conf. Inf., Comput. Social Syst. (ICCSS)*, Dalian, China, Jul. 2017, pp. 706–711.
[25] M. Benbaghdad, B. Fergani, and S. Tedjini, "Toward a new PHY layer scheme for decoding tags collision signal in UHF RFID system," *IEEE Commun. Lett.*, vol. 20, no. 11, pp. 2233–2236, Nov. 2016.
[26] *Handbook of Mathematical Functions: With Formulas, Graphs, and Mathematical Tables Applied Mathematics Series*, 2nd ed., National Bureau of Standards, Washington, DC, USA, 1964.
[27] D. B. K. Trieu and T. Maruyama, "An implementation of the mean shift filter on FPGA," in *Proc. 21st Int. Conf. Field Program. Logic Appl.*, Chania, Greece, Sep. 2011, pp. 219–224.

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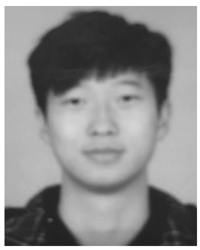

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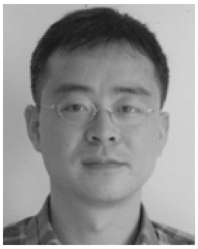

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