Robust Signal Detection in Passive RFID Systems

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Abstract **- This paper investigates a robust signal detection scheme for the uplink communication in radio frequency identification systems. An optimum maximum-likelihood sequence detector (MLSD) scheme and a sub-optimum sliding correlation detection scheme are proposed for differential bi-phase codes. The MLSD scheme has $3\,\mathrm{dB}$ performance improvement w.r.t. the single symbol ML detector. However, these algorithms are not robust to symbol timing errors, and the performance decreases fast already for few error samples. The robustness to timing errors can be significantly improved by a sub-optimum scheme performing one or more symbols sliding correlation detection.**

I. INTRODUCTION

In the recent years, there has been a growing interest in the development of communication systems for the identification and localization of objects [1]. Radio frequency identification (RFID) systems use radio frequency to identify, locate, and track people, objects, and animals [2].

An RFID system consists of readers and tags (or transponders), and depending on the operation mode, it can operate at different frequency bands. The tag, which is the data carrying device, can be active or passive, i.e., with or without an internal power source, and with a read-only or read-and-write memory. Identification systems operating at low frequencies, e.g., 125 KHz or 13.56 MHz, work by using the Faraday's principle of magnetic induction, and are limited in distance for physical reasons. Inductive coupling is only possible in the near-field of the reader antenna, where tags send data back to the reader using load modulation [2]. At higher frequencies, e.g., 900 MHz or 2.4 GHz, tags based on far-field emissions capture electromagnetic waves and transmit data using the backscattering principle [3]. In general, microwave passive or active backscatter tagging systems have a larger transmission distance than inductive systems. The choice of the operating frequency depends on the system's environment and requirements.

The performance of an RFID system is highly application dependent, i.e., tag-reader designs look different for different target applications. Depending on various parameters, like e.g. the environment, the operating frequency, the antenna size and shape, the signal bandwidth, and the signal-to-noise ratio (SNR), the performance of the system can change. Important aspects for measuring the performance are the maximum reading range and the identification time. The performance of RFID tags, for both near- and far-field has been discussed in [4]. Fundamental constraints limiting the performance of a system operating at different frequencies using passive tags have been presented in [5,6]. In [7], the propagation effects for UHF passive RFID systems have been analyzed. Some works addressing the multiple tag identification problem have been proposed in [8,9]. In the uplink (from tag to reader), conditions and requirements are somewhat different from the downlink (from reader to tag), and depending on the implementation, amplitude or phase are varied. Special coding schemes are used to ensure a continuous power supply to the tag, like e.g. Manchester, Miller or differential bi-phase (DBP) [2]. At the reader side, the received signal data levels are very low due to the low energy coding scheme, and sometimes the signal detection becomes a difficult task. None of the above contributions take into account the encoding and decoding schemes but rather consider "physical" limitations.

In this paper, we investigate a robust signal detection scheme for the uplink in passive RFID systems. Compared to the standard symbol-by-symbol detection, the proposed scheme is robust to symbol timing errors which is a limiting performance factor. This approach is useful for digital signal processing (DSP)-based RFID readers operating in the near- or far-field. The rest of the paper is organized as follows. In Sect. II., we describe the operation principle of the backscatter modulation in RFID systems. Basic and advanced detection schemes are derived in Sect. III.. Numerical results characterizing the performance gains are presented in Sect. IV., and conclusions are drawn in Sect. V..

II. SYSTEM DESCRIPTION

We consider the backscattered RFID transmission set-up sketched in Fig. 1. The reader starts to emit a continuous RF carrier wave

$$x_C(t) = \mathrm{Re}\left[A_C e^{j2\pi f_C t}\right],$$

where $\mathrm{Re}[\cdot]$ denotes the real operator, and A_C and f_C denote the amplitude and the frequency of the carrier, respectively. When a passive tag enters the RF field of the reader and has received enough energy, the incident waves are backscatter modulated by the data signal

$$s(t) = \sum_{n=1}^{N_S} S_n p\left(\frac{t - nT_S/2}{T_S}\right),$$

where $\{S_n\}$ is the coded symbol sequence, N_S is the number of symbols to be transmitted, T_S is the duration of a symbol, and the signal pulse $p(\cdot)$ is defined by

$$p\left(\frac{t}{T_S}\right) = \mathrm{rect}\left(\frac{t}{T_S}\right) = \begin{cases} 1 & \text{if } -T_S/2 \leq t \leq T_S/2, \\ 0 & \text{otherwise.} \end{cases}$$

Thus, the backscatter modulated signal can written as

$$x_{BS}(t) = \mathrm{Re}\left[\tilde{m}(s(t))e^{j(2\pi f_C t + 2\phi)}\right],$$

where $2\phi = 2\frac{2\pi}{\lambda}D$ is the phase delay, λ is the wavelength, D is the distance between the reader and the tag, and $\tilde{m}(s(t))$ denotes the modulation index of the backscattering cross-section. In general, an analytical expression of this modulation index is difficult to obtain. In the following, the knowledge of an exact expression of $\tilde{m}(\cdot)$ is of minor importance, and therefore, $\tilde{m}(\cdot)$ is replaced by the modulation index m of the modulating data signal. The backscatter modulated signal can be approximated by

$$x_{BS}(t) \approx \mathrm{Re}\left[A_{BS} m s(t) e^{j(2\pi f_C t + 2\phi)}\right],$$

with $m = \frac{\sigma_{max} - \sigma_{min}}{\sigma_{max} + \sigma_{min}}$, where the terms σ_{max} and σ_{min} refer to the maximum and minimum backscattering cross-sections [10]. After a low-noise amplifier (LNA), a down-conversion with conversion factor K' is performed yielding

$$x_{BB}(t) = K' m s(t) \cos(2\phi).$$

Homodyne detection of a double sideband modulated signal causes however an undesired phase difference 2ϕ, which may lead to the cancellation of the demodulated signal. We assume that the baseband signal $x_{BB}(t)$ is not cancel out by this phase difference, and for a given λ and D, the down-converted signal embedded in noise is given by

$$y(t) = x_{BB}(t) + \omega(t) = K s(t) + \omega(t),$$

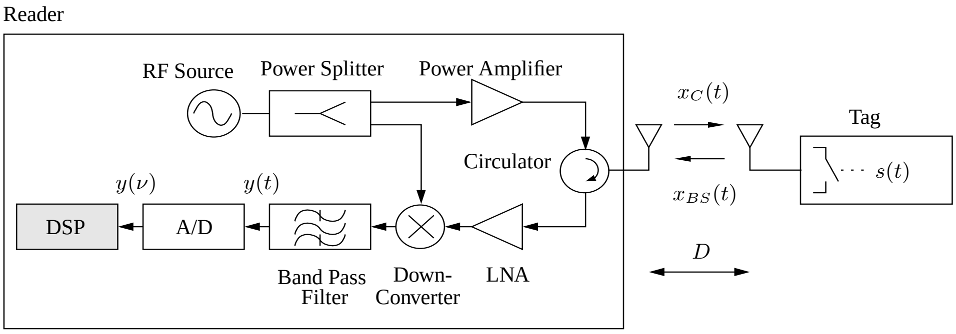

FIGURE 1 - RFID SYSTEM USING BACKSCATTERING MODULATION.

with $K = K'm\cos(2\phi)$. The noise signal $\omega(t)$ is modelled as zero-mean additive white Gaussian noise (AWGN) process with $\mathrm{E}[\omega(t+\tau)\omega(t)] = \frac{N_0}{2}\delta(\tau)$, where $\frac{N_0}{2}$ denotes the noise power spectral density. The received signal is passed through an analog-to-digital (A/D) converter, whose output sequence $\{y(\nu)\}$, consisting of samples

$$y(\nu) = Ks(\nu) + \omega(\nu), \quad \nu = 1, \dots, NN_S,$$

is the received signal $y(t)$ sampled at time instants $t = \nu\frac{T_S}{N}$, where N is the number of samples/coded symbol and the discrete AWGN is assumed to be statistically independent, Gaussian distributed random variable with zero-mean and equal variance $\frac{N_0}{2}$. Thus, the signal is fed to the DSP which detects and decodes the data signal.

III. DETECTION SCHEMES

We assume a coherent communication system, and investigate different detection schemes for DBP codes. In a similar way, these schemes could be also derived for other codes like e.g. Miller codes. In the DBP encoding scheme, a "0" is coded by a transition in the half bit period, and a "1" is coded by a lack of a transition. Since at the start of every symbol the level is inverted, for the n-th symbol, we have two possible "0" waveforms, i.e.,

$$S_n^1 = \begin{cases} -1 & 0 \le t \le T_S/2 \\ 1 & T_S/2 < t \le T_S \end{cases} \quad \text{or} \quad S_n^2 = -S_n^1,$$

and two possible "1" waveforms, i.e.,

$$S_n^3 = -1 \quad 0 \le t \le T_S \quad \text{or} \quad S_n^4 = -S_n^3,$$

where the "0" waveforms are orthogonal to the "1" waveforms. Here, a coded symbol depends only on the coded symbol of the previous interval, and the sequence of symbols $\{S_n\} = \{S_n^k\}$, for a given sequence of indices $k \in \{1, \dots, 4\}$, is a first-order Markov process.

This process is completely described by the transition matrix $\boldsymbol{P}_n$, in which an element $p_{ji} = p(j|i)$ equals the conditional probability of the symbol j occuring after a given symbol i has occured. For DBP codes, this matrix is given by

$$\boldsymbol{P}_n = \begin{bmatrix} p_{S_n^1 S_n^1} & p_{S_n^1 S_n^2} & p_{S_n^1 S_n^3} & p_{S_n^1 S_n^4} \\ p_{S_n^2 S_n^1} & p_{S_n^2 S_n^2} & p_{S_n^2 S_n^3} & p_{S_n^2 S_n^4} \\ p_{S_n^3 S_n^1} & p_{S_n^3 S_n^2} & p_{S_n^3 S_n^3} & p_{S_n^3 S_n^4} \\ p_{S_n^4 S_n^1} & p_{S_n^4 S_n^2} & p_{S_n^4 S_n^3} & p_{S_n^4 S_n^4} \end{bmatrix} = \begin{bmatrix} 0.5 & 0 & 0 & 0.5 \\ 0 & 0.5 & 0.5 & 0 \\ 0.5 & 0 & 0 & 0.5 \\ 0 & 0.5 & 0.5 & 0 \end{bmatrix}.$$

3.1 Symbol-by-Symbol Detection

Let $\boldsymbol{S}^k$, $k = 1, \dots, 4$, be the vectors containing the N sampled values of the waveforms "0" and "1". As a consequence of the properties of the AWGN process $\omega(\nu)$, the correlation outputs

$$R_n^k = \left\langle [y(1+N(n-1)), \dots, y(Nn)], \boldsymbol{S}^k \right\rangle, \quad \forall k, n, \tag{1}$$

represent a sufficient statistic for the estimation problem [11], where $\langle \mathbf{a}, \mathbf{b} \rangle$ denotes the inner product of two vectors $\mathbf{a}$ and $\mathbf{b}$. Using a maximum-likelihood (ML) detector we have

$$\hat{S}_n = \underset{k}{\operatorname{argmax}} \; R_n^k, \quad \forall n.$$

Consider the signal space of a DBP encoding scheme (Fig. 2) in which the four possible points are $S_n^1 = S_n^3 = -S_n^2 = -S_n^4 = \sqrt{E_b}$, where E_b is the energy per bit.

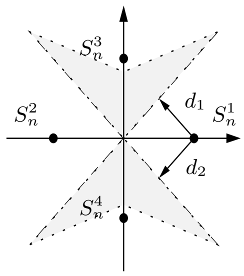

FIGURE 2 - SIGNAL SPACE FOR DBP SIGNALS.

To derive analytically a closed-form expression of the bit-error probability (BEP), we assume that S_n^1 was transmitted, and we investigate the symbol-error probability (SEP) $P\left(\mathrm{error}|S_n^1\right)$ which equals to the BEP $P_{\mathrm{b,ML}}$. Since "0" symbols are orthogonal to "1" symbols we have

$$\begin{aligned} P\left(\mathrm{error}|S_n^1\right) = {} & P\left(d_1 > \frac{\sqrt{2E_b}}{2}\right) P\left(d_2 < \frac{\sqrt{2E_b}}{2}\right) \\ & + P\left(d_2 > \frac{\sqrt{2E_b}}{2}\right) P\left(d_1 < \frac{\sqrt{2E_b}}{2}\right). \end{aligned}$$

With

$$d_i' = d_i \frac{1}{\sqrt{N_0/2}} \gtrless \frac{\sqrt{2E_b}}{2} \frac{1}{\sqrt{N_0/2}} = \sqrt{\frac{E_b}{N_0}}, \quad i = 1, 2,$$

we can write

$$P\left(\mathrm{error}|S_n^1\right) = 2\mathrm{Q}\left(\sqrt{\frac{E_\mathrm{b}}{N_0}}\right) \left[1 - \mathrm{Q}\left(\sqrt{\frac{E_\mathrm{b}}{N_0}}\right)\right] = P_{\mathrm{b,ML}},$$

where $\mathrm{Q}(x)$ is the Q-function [11]. Since DBP signals have memory, i.e., symbols transmitted in successive intervals are *not* independent, the above ML detection scheme is not optimum. Utilizing the fact that only certain sequence of symbols are allowed, the detection scheme can be enhanced.

We propose a ML sequence detector (MLSD) scheme which is computed in two steps:

Trace forward step: First, the correlation values in each signal interval for the four waveforms are calculated using (1), and are stored in a data structure called trellis (Fig. 3), where the transitions between symbols are described by the matrix $\boldsymbol{P}_n$. Second, the best preceding symbol, i.e., the one which is possible and has the highest correlation

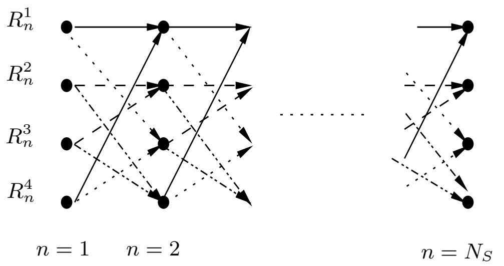

FIGURE 3 - TRELLIS USED IN THE MLSD OF DBP CODES.

value is determined for all k and $n>2$, and the new correlation values are computed according to

$$\begin{aligned}\tilde{R}_n^1 &= R_n^1 + \max\{R_{n-1}^1, R_{n-1}^4\},\\ \tilde{R}_n^2 &= R_n^2 + \max\{R_{n-1}^2, R_{n-1}^3\},\\ \tilde{R}_n^3 &= R_n^3 + \max\{R_{n-1}^1, R_{n-1}^4\},\\ \tilde{R}_n^4 &= R_n^4 + \max\{R_{n-1}^2, R_{n-1}^3\},\end{aligned}$$

and stored in the trellis.

Trace back step: The bit stream is assembled by iterating trough the trellis starting from the end. We start by choosing the resulting highest correlation value, and we use the trellis created in the forward step for always choosing the best predecessor.

If the DBP encoding scheme is represented by a recursive encoder with rate $R_\mathrm{c}=1/2$ where "0" and "1" are coded to two antipodal half waveforms, the minimum Hamming distance of the code is $d_\mathrm{min}=2$. Thus, at high SNR, the asymptotic BEP can be approximated by

$$\mathrm{Q}\left(\sqrt{2d_\mathrm{min}R_\mathrm{c}\frac{E_\mathrm{b}}{N_0}}\right) = \mathrm{Q}\left(\sqrt{\frac{2E_\mathrm{b}}{N_0}}\right) \leq P_\mathrm{b,MLSD}. \qquad (2)$$

In Sect. IV., it is shown that the derived lower bound is close to numerical results (at high $\frac{E_\mathrm{b}}{N_0}$), and the MLSD scheme performs $3\,\mathrm{dB}$ better than the ML detector.

However, these schemes are very sensitive to symbol timing errors, and the system performance can decrease quickly as it is shown in the simulation results. The robustness to timing errors can be significantly improved by a sub-optimum scheme performing a symbol sliding correlation detection.

3.2 Sliding Detection

We consider the received signal zero padded to length NN_S+N-1 given by

$$\begin{aligned}\tilde{\mathbf{y}} &= [\tilde{y}(1),\ldots,\tilde{y}(NN_S+N-1)]\,,\\ &= [0,\ldots,0,y(1),\ldots,y(NN_S)].\end{aligned}$$

The correlations are calculated by sliding the received signal and computing the correlations at each sample shift ν with the different waveforms, i.e.,

$$R_n^k(\nu) = \left\langle [\tilde{y}(\nu),\ldots,\tilde{y}(\nu+N-1)]\,, \boldsymbol{S}^k \right\rangle, \qquad \forall \nu.$$

Thus, the ML detector makes a decision in each signal interval of length N according to

$$\hat{S}_n = \arg \max_{\substack{k\\ \nu\in\{1+N(n-1),\ldots,Nn\}}} \{R_n^k(\nu)\}, \qquad \forall n.$$

The MLSD scheme is similar to the one described above. In this case, during the trace forward step the maximum correlation values in each symbol interval are calculated by

$$R_n^k = \max_{\nu\in\{1+N(n-1),\ldots,Nn\}} \{R_n^k(\nu)\}, \qquad \forall k,n,$$

and stored in the trellis. The rest of the algorithm is the same as the one in Sect. 3.1.

The sub-optimum sliding detection scheme can be improved in two ways. First, the analysis can be extended by considering two (or more) symbols in the sliding correlations, i.e., $\boldsymbol{S}^1\boldsymbol{S}^1$, $\boldsymbol{S}^1\boldsymbol{S}^3$, $\boldsymbol{S}^3\boldsymbol{S}^1$, $\boldsymbol{S}^3\boldsymbol{S}^3$ and $\boldsymbol{S}^2\boldsymbol{S}^2$, $\boldsymbol{S}^2\boldsymbol{S}^4$, $\boldsymbol{S}^4\boldsymbol{S}^2$, $\boldsymbol{S}^4\boldsymbol{S}^4$, and as it is shown in Sect. IV., the system performance is improved. However, for increasing the number of symbols, the complexity of the correlator increases exponentially. A few more effort on synchronization will decrease the timing errors and then reduce the complexity for the sliding detection scheme. Second, the nature of DBP codes would suggest to use the known half-bit before and after each waveform to improve the performance of the correlation.

IV. SIMULATION RESULTS

In the simulation results, we validate the analysis and investigate the achievable performance gains resulting from the presented detection schemes. We consider an RFID system with $N=32$ and $N_S=128$, employing DBP codes in the uplink communication, where the data transmitted by the tag is randomly generated.

The achievable performance gains resulting from the schemes in Sect. III. can be seen in Fig. 4 for different symbol correlations. The figure displays the bit-error rate (BER) at the decoder output as a function of the received SNR. In addition, the derived analytical expressions are also shown in the same figure.

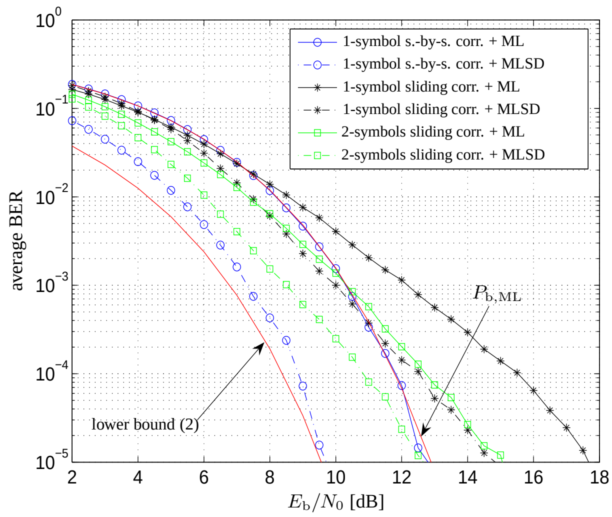

FIGURE 4 - AVERAGE BERS APPLYING SYMBOL-BY-SYMBOL AND SLIDING DETECTIONS.

Note that the BER curves using the MLSD show a larger slope for increasing SNR values than using the ML detector. As expected, for 1-symbol correlation, the scheme in Sect. 3.1 outperforms the scheme in Sect. 3.2, where the best performance is given by the symbol-by-symbol correlation with MLSD.

Using more symbols in the sliding detection scheme we approach the lower bound in (2), where the 2-symbols sliding correlation with MLSD is already better than $P_\mathrm{b,ML}$. However, the relative gain between MLSD and ML decreases for increasing the number of used symbols in the correlation.

In Fig. 5, the performance of the system in terms of BER (Fig. 4) is translated in number of corrected decoded data signals. The figure displays the percentage of received signals that can be decoded without errors. The figure shows that at $7.5\,\mathrm{dB}$, it is already possible to correctly decode 95% of the received signals using the symbol-by-symbol correlation with MLSD scheme, 80% using the 2-symbols sliding correlation with MLSD, and only 10% using both 1-symbol correlation

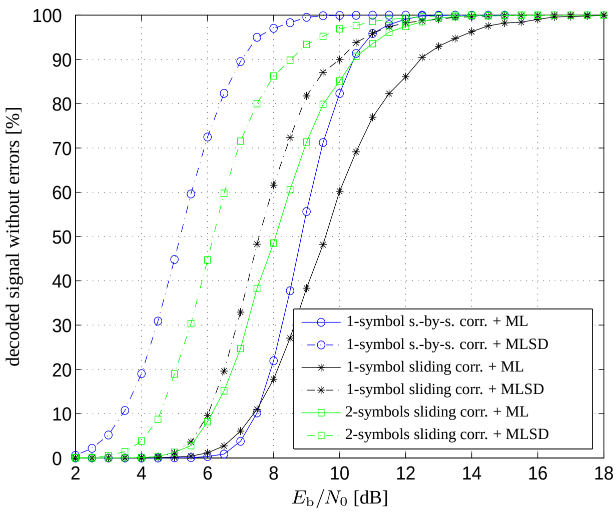

FIGURE 5 - PERCENTAGE OF DECODED DATA SIGNALS WITHOUT ERRORS APPLYING SYMBOL-BY-SYMBOL AND SLIDING DETECTIONS.

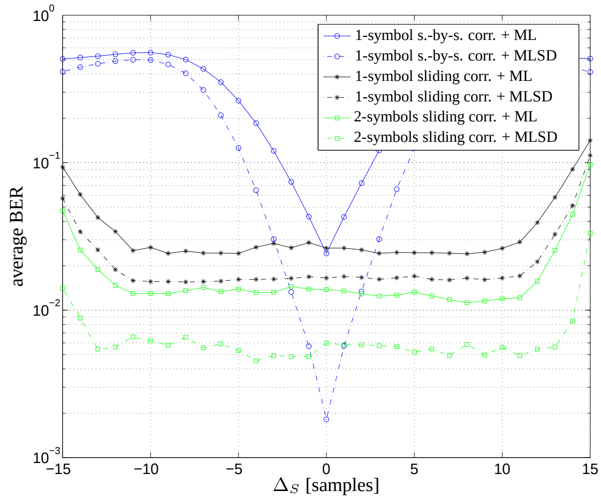

FIGURE 6 - AVERAGE BERS AT $7\,\mathrm{dB}$ APPLYING SYMBOL-BY-SYMBOL AND SLIDING DETECTIONS AS A FUNCTION OF THE TIME SAMPLE ERRORS.

with ML schemes. Further improvements are to be expected from an additional error detection and correction scheme at the expense of an higher complexity.

The influence of symbol timing errors is examined in Fig. 6 for the schemes in Sect. III. at $E_b/N_0 = 7\,\mathrm{dB}$. The figure shows the BER degradation as a function of the timing error Δ_S expressed in number of shift samples, where $\Delta_S = 0$ implies perfect symbol synchronization.

We can see that the symbol-by-symbol detection schemes are very sensible to timing errors. For $|\Delta_S| = 1$, the symbol-by-symbol correlation with MLSD has the same performance than the 2-symbols sliding correlation with MLSD, and for $|\Delta_S| > 1$ the best performance is given by the sliding scheme.

It turns out that using sliding detection schemes, the system is robust to timing errors, and we observe a constant average BER for at least $|\Delta_S| \leq 10$. Correlation schemes using 2-symbols are more robust than correlations using only 1-symbol, and with MLSD we arrive to support timing errors up to $|\Delta_S| = 14$ maintaining a constant BER. For $\Delta_S > N/2 - 1$ and $\Delta_S < -N/2$, the performance gain is significantly smaller since some maximum correlation values are shifted in the next time slot destroying the signal detection.

V. CONCLUSIONS

A robust signal detection scheme with moderate complexity minimizing the BER in RFID systems has been derived. The symbol-by-symbol correlation with MLSD improves the system performance by $3\,\mathrm{dB}$ w.r.t. conventional ML detectors. The increased slope of the BER makes the MLSD scheme attractive in RFID systems where the power is limited. However, these schemes are not robust to symbol timing errors and the 2-symbols sliding correlation with MLSD scheme has the best performance already for few error samples. This approach leads to often desired asymmetry in complexity, with sophisticated signal processing hardware in the reader, and cheap data processing in the tag.

The proposed scheme is robust to symbol synchronization errors, and it is suited for improving the reading distance and signal detection in a possible combination with an error detection and correction scheme.

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