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Improved Detection Metric and Oversampling-based Frame Detector for DSRC Receiver

Xiang Li[1*], Fuqiang Liu[1] and Nguyen Ngoc Van[2]

[1] *School of Electronics and Information Engineering, Tongji University, Shanghai, 201804, China.*
[2] *School of Electronics and Telecommunications, Hanoi University of Science and Technology, Hanoi, Vietnam.*

Abstract

In inter-vehicle communication systems based on dedicated short-range communications (DSRC), frame detection is essential for the correct demodulation of a received frame. Owing to the fast mobility of vehicles and the relatively high radio frequency carrying DSRC signals, the frame detection reliability suffers from low signal-to-interference-plus-noise ratio (SINR) and time-varying noise and interference. To address this issue, this study proposed a new detection method to improve the reliability of DSRC receivers in highly dynamic outdoor environments. Specifically, a novel detection metric based on autocorrelation was first proposed to achieve a low and stable probability of false alarm (PFA). Then, the oversampling technique was employed to improve the detection probability (PD) in low-SINR regimes. Finally, a reference design was also presented on a field-programmable gate array (FPGA) for the proposed scheme. Simulation results demonstrated that both low PFA and high PD can be achieved simultaneously in vehicular communications by using the proposed method. Results given by the hardware implementation based on FPGA agree that the feasibility and complexity of our method is acceptable.

Keywords: Dedicated short-range communications; Frame detection; Oversampling; Wireless receiver

1. Introduction

Dedicated short-range communications (DSRC) is considered as an essential technology for any future intelligent transportation system. By enabling high-speed data exchange between vehicles through wireless communications, DSRC enhances the safety and efficiency of transportation systems. Currently, the most common worldwide DSRC standard is IEEE 802.11p [1]. This new wireless communication standard of the IEEE 802.11 family adopts orthogonal frequency division multiplexing (OFDM) technology in its physical layer to achieve high spectrum efficiency, high data rate, and strong robustness in frequency-selective fading channels. According to IEEE 802.11p, a receiving frame is composed of several OFDM symbols in the time domain and must be demodulated symbol-by-symbol using a windowed fast Fourier transform (FFT) in the receiver. Before any further processing, symbol timing synchronization, which is used to locate the FFT window of each OFDM symbol, must be achieved to avoid inter-symbol interference. Symbol timing synchronization is usually a two-step procedure. The first step is frame detection, which is used to locate the beginning of the transmitting frame. The second step is fine symbol timing estimation, which allows the FFT window of each OFDM symbol to be located accurately. This study, which adheres to the IEEE 802.11p standard, focuses on the frame detection problem for DSRC receivers.

In vehicular communications, two basic problems degrade the accuracy of frame detection: dynamic noise and interference and relatively low signal-to-interference-plus-noise ratio (SINR). On one hand, due to the high mobility of vehicles, the power of noise and interference that superimposes upon received signal changes rapidly with time. On the other hand, DSRC radio signal is easily blocked by buildings, trees, or other vehicles. For example, if two cars are approaching an intersection at 50 km/h, only 30% of all intersection corners provide line-of-sight at a desired warning point of three seconds to a potential impact [2]. In other words, received signals suffer lower SINR compared with traditional wireless communications, and the receiver must recognize the frame signal in a relatively low SINR regime with acceptable detection probability (PD).

2. State of the art

Signal detection serves as the first, and a very important, stage of receiver processing because it decides whether the entire receiver should be activated and coarsely locates the header of the incoming packet. Traditional algorithms for signal detection fall into three classes: 1) Autocorrelation based detection (ACD) algorithms [3]–[9], where the autocorrelation between identical portions of the preamble is used to perform the signal detection. 2) Blind-detection (BD) algorithms [10]–[12], where the frame is detected by evaluating if its power is above a predefined threshold or if its baseband signal has a specific pattern. 3) Matched-filter-based detection (MFD) algorithms [13], where the received signal is correlated with the known preamble sequence, and the frame is detected if the correlation value exceeds a predefined threshold.

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Among the above algorithms, the BD algorithms (except for energy-detection-based algorithms [14]) usually have higher implementation complexity, and their performances normally are not as good as those of the MFD and ACD algorithms owing to their lack of using known preamble patterns. The best performance can be achieved using the MFD methods. Their high hardware complexity, however, makes them less suitable for FPGA-based detector implementation. Moreover, as the optimal detection threshold of MFD algorithms has to be determined by the SINR, this threshold is difficult to specify because of the fast changing characteristics of SINR in vehicle communication environments. Compared with the BD and MFD methods, the ACD algorithms have moderate performance and implementation complexity. Given that the average power of the received signal can be used to normalize its autocorrelation value, the decision threshold of ACD algorithms is also easy to specify irrespective of SINR.

For DSRC receivers, frame detection is usually performed by using ACD algorithms. A preamble sequence at the front of each frame aids its delivery in the IEEE 802.11p standard [1] and usually consists of several repeated pseudo-random training symbols. High autocorrelation is used in many traditional symbol synchronization methods because it distinguishes training symbols from noise, interference, and other OFDM symbols. In [3], Schmidl and Cox used autocorrelation between two identical parts of a periodic training symbol to estimate symbol timing. A method using multiple training symbols to enhance the robustness of symbol synchronization was presented in [4]. A joint frame detection and timing estimation scheme was proposed in [5] to manage doubly selective channels. A novel solution in which frame detection is accomplished in the frequency domain on the basis of a suitable likelihood ratio test was presented in [6]. Giving consideration to transmitter and receiver mobility, [7] presented a robust symbol timing estimation algorithm for pilot-aided OFDM systems in mobility fading environments, and [8] proposed a frame detection method to manage frequency-selective channels. From the viewpoints of hypothesis testing and classification, [9] proposed a synchronization approach using the fourth-order statistics of training symbols to decrease the probability of false alarm (PFA). However, the aforementioned methods were usually used in relatively high SINR regimes, and acceptable detection performances could not be achieved by using them in low SINR regimes that occur frequently in vehicular communications. In this study, we propose a practical method based on an oversampling technique to improve detection performance for DSRC receivers in low SINR regimes.

The remainder of this paper is organized as follows. Section 3 described the proposed detection method, which includes the system model used in this work, the proposed detection metric, the oversampling-based detection scheme, and the FPGA-based hardware implementation of the proposed detector. Section 4 presents the simulation and implementation results of our method. Section 5 concludes this paper.

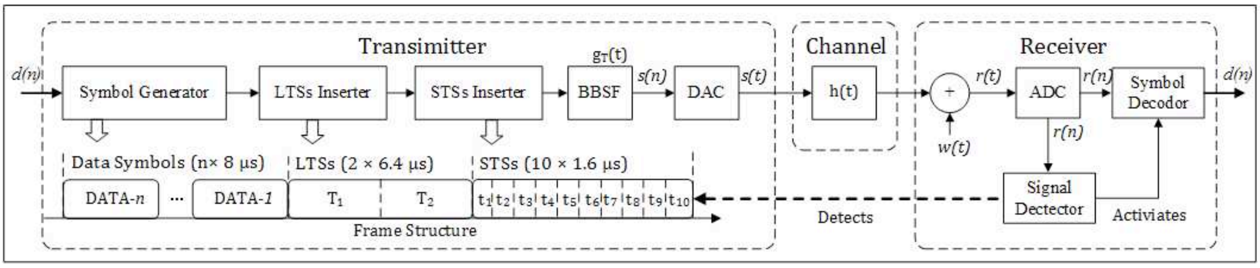


Fig. 1. Block diagram of the IEEE 802.11p transceiver and frame structure (adapted from [1])

3. Methodology

A novel frame detection method based on signal oversampling is proposed in this section. We first present the system model used in this study, and then propose a frame-detection metric to manage the dynamic noise and interference. Next, we use oversampling to increase the PD for low SINR while maintaining a low-level PFA. The implementation of the proposed method based on the FPGA platform is discussed at the last part of this section.

3.1 System model

Figure 1 shows the block diagram of our reference DSRC transceiver. At the transmitter, physical layer service data are first divided into several groups, each of which is then transformed into an OFDM symbol through a series of processes: scrambling, convolution encoding, puncturing, interleaving, modulating, and a 64-point inverse FFT. Before the digital modulated sequence is converted into an analog signal, an application of a baseband shaping filter (BBSF) (i.e., which is composed of an up-sampler followed by a low-pass filter) is typically indispensable for the practical elimination of out-band interference in the transmitter. Let $s(n)$ denote the modulated baseband sequence, $g_T(t)$ be the unit impulse response (UIR) of the BBSF, and T_S be the sampling period ($T_S = 0.1\,\mu s$ under the IEEE 802.11p standard). Under the action of the BBSF and the digital-to-analog converter (DAC), the analog complex baseband signal to transmit is given as

$$s(t) = \sum_{n=0}^{N-1} s(n) g_T(t - nT_s) \tag{1}$$

Given a propagation through a wireless channel with the UIR $h(t)$, the received complex analog baseband signal $r(t)$ and its sampled sequence $r(n)$ in the receiver can be written respectively as

$$\begin{aligned} r(t) &= s(t) * h(t) + w(t) = \tilde{s}(t) + w(t),\ t \geq 0 \\ r(n) &= \tilde{s}(n) + w(n),\ n \geq 0 \end{aligned} \tag{2}$$

where $w(t)$ and $w(n)$ are the additive white Gaussian noise (AWGN) and its sampled sequence respectively, (*) denotes the convolution operator, $\tilde{s}(t) = s(t) * h(t)$, and $\tilde{s}(n)$ is the sampled sequence of $\tilde{s}(t)$.

At the receiver, a frame detector monitors the wireless channel to detect incoming frames, while the other function blocks of the receiver are typically inactive. Once the frame-header of an incoming frame is recognized by the frame detector, the entire receiver is activated, and then the inverse processes of the transmitter are performed on the received sequence, thus recovering the original data. To aid the delivery of frames, a physical layer convergence procedure preamble sequence, which is composed of both short training sequence (STS) and long training sequence (LTS) data, prefixes each frame, as shown in Figure 1. The STS is constructed by repeating a short training symbol 10 times (denoted by $t_1 : t_{10}$), where the short training symbol is a predefined pseudo-random sequence with a length of 16 samples. The STS can be utilized for signal detection, automatic gain control, and coarse receiver synchronization. The LTS consists of two repeated long training symbols (denoted by $T_1 : T_2$) and can be used for fine synchronization and channel estimation. To determine the presence of an STS within a received sequence, a binary function model is established,

$$H(n)=\begin{cases}1, & M(n)\geq\gamma \\ 0, & M(n)<\gamma\end{cases}, n\geq 0 \tag{3}$$

where $H(n)=1$ indicates that the STS appears in the received sequence at the instant n , g is a predefined threshold, and $M(n)$ is a detection metric determined by the received sequence.

Pseudo-randomness and periodicity distinguish STS from noise and interference. Thus, correlation-based detection metrics are used in numerous OFDM-based systems. Let $\Re(x,y,l,n)=\sum_{i=n-L+1}^{n}x^{*}(i)y(i-l)$ be the correlation of $x(i)$ and $y(i)$ [$x^{*}(i)$ is the complex conjugate of sequence $x(i)$], and the metric presented in [3] reads

$$M(n)=\left|\frac{R(n)}{P(n)}\right|^{2}=\frac{\Re^{2}(r,r,L,n)}{\Re^{2}(r,r,0,n)},\quad n\geq 0 \tag{4}$$

where L is the period of the STS ($L=16$ for 802.11p), and $R(n)$ and $P(n)$ respectively denote the autocorrelation function and the average power of the received signal. Differing from the second-order statistics used in [3], [9] proposed a novel metric based on fourth-order statistics and achieved good performance. However, these techniques do not generally provide an acceptable performance for vehicular communications because the working environment frequently exhibits low SINR, as well as rapidly time-varying noise and interference. Therefore, the key task of the detection problem in vehicular communications is to choose well a proper detection metric while adhering to the IEEE 802.11p standard. On one hand, the detection metric should be designed to immunize the PFA from rapidly time-varying noise and interference. On the other hand, it should be able to achieve a high PD and low PFA in relatively low SINR regimes.

In the rest of this paper, the boldface subscripts " $\mathbf{r}$ " and " $\mathbf{i}$ " are used to denote the real and imaginary parts of a scalar or vector respectively, the symbol " n " denotes the n^{th} sampling instant with a normal sampling frequency, and the symbol " m " denotes the m^{th} sampling instant with an oversampling frequency. Both n and m are positive integers.

3.2 Detection metric

Note that the correlation function defined in [3] can be rewritten as follows:

$$\begin{aligned}R(n)=&\left(\Re(r_{\mathbf{r}},r_{\mathbf{r}},L,n)+\Re(r_{\mathbf{i}},r_{\mathbf{i}},L,n)\right)\\&+j\left(\Re(r_{\mathbf{r}},r_{\mathbf{i}},L,n)+\Re(r_{\mathbf{i}},r_{\mathbf{r}},L,n)\right)\end{aligned} \tag{5}$$

According to the IEEE 802.11p, regardless of the existence of an STS, the imaginary part of $R(n)$ contributes nothing but noise and interference, degrading the accuracy of frame detection. In [9], wherein fourth-order statistics was used, a novel approach was presented to detect the preamble and a considerably lower PFA was achieved. However, too many hardware multipliers are involved in the implementation of this approach. In this paper, a fourth-order statistic based on autocorrelation is used to detect the STS preamble, the proposed correlation function is

$$R(n)=R_{\mathbf{r}}(n)R_{\mathbf{i}}(n)=\Re(r_{\mathbf{r}},r_{\mathbf{r}},L,n)\Re(r_{\mathbf{i}},r_{\mathbf{i}},L,n) \tag{6}$$

where $R_{\mathbf{r}}(n)$ and $R_{\mathbf{i}}(n)$ respectively denote the correlation function of the real and imaginary parts of the received sample $r(n)$.

Moreover, in [3] and [9], because the detection metric $M(n)$ is constructed using the average received power $P(n)$ to normalize the correlation function $R(n)$, a constant detection threshold is applicable for a given PFA, regardless of the power of noise and interference. Following these methods, the correlation function proposed in this study is normalized by the following $P(n)$:

$$P(n)=P_{\mathbf{r}}(n)P_{\mathbf{i}}(n)=\Re(r_{\mathbf{r}},r_{\mathbf{r}},0,n)\Re(r_{\mathbf{i}},r_{\mathbf{i}},0,n) \tag{7}$$

where $P_{\mathbf{r}}(n)$ and $P_{\mathbf{i}}(n)$ denote the average power of real and imaginary parts of the received signal $r(n)$. Accordingly, our detection metric is

$$M(n)=\frac{|R(n)|}{P(n)}=\frac{|R_{\mathbf{r}}(n)R_{\mathbf{i}}(n)|}{P_{\mathbf{r}}(n)P_{\mathbf{i}}(n)}, n\geq 0 \tag{8}$$

As aforementioned, if the active signal in the received sequence is STS, the real part of the correlation should be a constant value, we then have

$$\begin{aligned}&\Re(\hat{s}_{\mathbf{r}},\hat{s}_{\mathbf{r}},L,n)=\Re(\hat{s}_{\mathbf{i}},\hat{s}_{\mathbf{i}},L,n)=L\sigma_s^2/2\\&\Re(\hat{s}_{\mathbf{r}},\hat{s}_{\mathbf{r}},0,n)=\Re(\hat{s}_{\mathbf{i}},\hat{s}_{\mathbf{i}},0,n)=L(\sigma_s^2+\sigma_w^2)/2\end{aligned} \tag{9}$$

where σ_s^2 is the average power of the received STS, and σ_w^2 is the average power of the noise and interference. According to Equation (9), the correlation function of the real part of the received sequence is

$$R_{\mathrm{r}}(n) = L\sigma_s^2/2 + \Re(w_{\mathrm{r}}, w_{\mathrm{r}}, L, n) + \Re(\hat{s}_{\mathrm{r}}, w_{\mathrm{r}}, L, n) + \Re(w_{\mathrm{r}}, \hat{s}_{\mathrm{r}}, L, n) \quad (10)$$

In Equation (10), the second item is the sum of L independent and identical distributed (IID) random variables with zero mean and variance $\sigma_w^4/4$. The third and fourth items are the linear combination of L IID Gaussian random variables with zero mean and variance $\sigma_w^2/4$. The same situation with $R_{\mathrm{r}}(n)$ applies to the $R_{\mathrm{i}}(n)$. According to the central limit theorem [14], we can determine the mean values of both $R_{\mathrm{r}}(n)$ and $R_{\mathrm{i}}(n)$:

$$\mu_R = E[R_{\mathrm{r}}(n)] = E[R_{\mathrm{i}}(n)] = L\sigma_s^2/2 \quad (11)$$

Following a similar derivation, the mean value of $P_{\mathrm{r}}(n)$ and $P_{\mathrm{i}}(n)$ can be written as

$$\mu_P = E[P_{\mathrm{r}}(n)] = E[P_{\mathrm{i}}(n)] = L^2\left(\sigma_s^2 + \sigma_w^2\right)^2/4 \quad (12)$$

For the proposed metric $M(n)$, as the standard deviation of the denominator $P(n)$ is usually lesser than its mean value, the following approximation can be used:

$$M(n) \approx \frac{4\left|R_{\mathrm{r}}(n)R_{\mathrm{i}}(n)\right|}{L^2\left(\sigma_s^2 + \sigma_w^2\right)^2} \quad (13)$$

When Equations (11), (12), and (13) are combined, after basic derivation, the mean value of the proposed metric reads

$$E[M(n)] \approx \left(\frac{\sigma_s^2}{\sigma_s^2 + \sigma_w^2}\right)^2 = \left(\frac{\beta}{\beta+1}\right)^2 \quad (14)$$

where $\beta = \sigma_s^2/\sigma_w^2$ denotes the SINR of the receiving sequence. Thus, the mean value of the metric $M(n)$ can clearly be utilized to estimate the SINR.

To determine the threshold for a specified PFA, the case where the active signal in the received sequence is nothing but noise and interference is analyzed. The detection metric $M(n)$ can be rewritten as

$$M(n) = \left(2/(L\sigma_w^2)\right)^2 \left|\Re(w_r, w_r, L, n)\Re(w_i, w_i, L, n)\right| \quad (15)$$

$M(n)$ is the product of two IID Gaussian distributed variables with mean zero and variance $1/L$. Let $K_0(*)$ denote the modified Bessel function of the second kind. Hence, the probability density of $M(n)$ becomes [15]

$$p_P(x) = 2L/\pi \cdot K_0(|Lx|) \quad (16)$$

Therefore, the PFA can be obtained from

$$P_F(n) = P_r\{|x| > \gamma\} = \frac{2L}{\pi}\int_\gamma^\infty K_0(|Lx|)dx = Q_K(L\gamma) \quad (17)$$

where γ is the given decision threshold, and $Q_K(x)$ can be calculated using numerical integration. With the proposed detection metric, PFA depends only on the predefined threshold, not the noise and interference.

3.3 Oversampling

For the proposed detection metric, because the detection performance improves with increasing correlation length, a solution to improve PD while maintaining a low level PFA is to adopt a large correlation length L. However, only 2 to 3 short training symbols are available for signal detection by the receiver [16]. Moreover, the increased correlation length imposes additional processing delay and complicates the implementation. Improved detection performance can also be achieved by oversampling, by which the analog time-domain baseband signal is over-sampled at a frequency Kf_s, where $f_s = 1/T_s$ is the transmitter sampling frequency, and K (the oversampling rate) is an integer greater than one. Let $g(t) = g_T(t) * h(t)$ denote the UIR of the subsystem from the output port of the modulator of the transmitter to the input port of the frame detector of the receiver. According to equation (2), the receiving analog complex baseband signal is,

$$r(t) = \sum_{l=0}^{LN_{\mathrm{sts}}-1} s(l)g(t - lT_s) + w(t) \quad (18)$$

Let $T_K = T_s/K$ denote the sampling period in the receiver. If the analog signal $r(t)$ is over-sampled at a frequency of Kf_s, the received sequence reads,

$$r(m) = \sum_{l=0}^{LN_{\mathrm{sts}}-1} s(l)g(mT_K - lT_s) + w(mT_K) \quad (19)$$

Let n and k respectively denote the integer and the remainder of m/k; obviously $m = nK + k$ and $k \in [0, K-1]$. According to different values of k, the received sequence $r(m)$ can be split into K branches, and each of them can be treated as a received sequence that is normal-sampled at the frequency f_s. The received sequence of the k^{th} branch is defined as,

$$r_k(n) = r(nK + k) = \sum_{l=0}^{LN_{\mathrm{sts}}-1} s(l)g\left((n-l)T_s - kT_K\right) + w(nT_s + kT_K) \quad (20)$$

To simplify the analysis, we assume that the UIR of the BBSF in the transmitter, $g_T(t)$, is a rectangular pulse with width T_s and amplitude one, and the wireless propagation channel is an ideal AWGN channel with an UIR of $h(t) = 1$. Thus we have,

$$r_k(n) = s(n) + w_k(n) \quad (21)$$

where $w_k(n) = w(nT_s + kT_K)$. Let $H_k(n)$ denote the decision obtained by applying the proposed detection metric (8) to the k^{th} branch. P_{Fb} denotes the PFA that is specified for each of the branches, and the detection threshold γ_b can be found by applying equation (17) on the P_{Fb}. Thus we have,

$$H_k(n) = \begin{cases} 1, & M_k(n) \geq \gamma_b \\ 0, & others \end{cases} \tag{22}$$

where $M_k(n)$ is obtained by applying the proposed detection metric (8) to the received sequence of the branch $r_k(n)$. Therefore, we have K branch-decisions with the same confidence level.

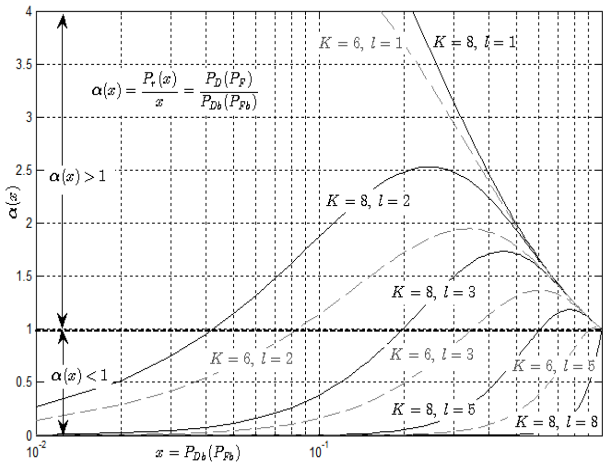


Fig. 2. $\alpha(x)$ for different *l* with $K = 6$ and $K = 8$

In order to obtain a final decision, the *l*-out-of-*K* rule is employed to combine all of the branch-decisions, by which the assertion that the STS preamble is present in the received sequence is made as long as more than l branches among $r_0(n)$: $r_{K-1}(n)$ declare such to be the case. According the *l*-out-of-*K* rule, the final decision can be expressed as,

$$\tilde{H}(n) = \begin{cases} 1, & \sum_{k=0}^{K-1} H_k(n) \geq l \\ 0, & others \end{cases} \tag{23}$$

Consequently, the final P_F and P_D can be elicited. Let P_{Db} be the branch PD determined by the threshold γ_b. The relationships between P_F and P_{Fb}, or P_D and P_{Db}, are subject to the same function,

$$P_r(x) = 1 - \sum_{m=0}^{l-1} \binom{K}{m} x^m (1-x)^{K-m} \tag{24}$$

where $\binom{K}{m} = \frac{K!}{m!(K-m)!}$ is the combinatorial number for *m*-out-of-*K*. The variable x denotes the branch probability (P_{Fb} or P_{Db}), and $P_r(x)$ is the corresponding final probability (P_F or P_D) after combining decisions.

Detection performance is affected directly by parameters l and K. In order to analyze the effect of the decision combination, let

$$\alpha(x) = \frac{P_r(x)}{x}, 0 < x < 1 \tag{25}$$

be the magnification of the branch probability. If $\alpha(P_D) > 1$ holds, P_D will be promoted by use of oversampling; otherwise, P_D will be degraded. The same law applies to P_{Fb} and P_F.

Figure 2 shows the $\alpha(x)$ function for different l and K regimes. Considering that P_{Fb} is very small while P_{Db} is typically of sufficient value that we can obtain the following conclusions. First, if a smaller integer value is specified for l (such as $l = 1$), P_D can be improved significantly; P_F is simultaneously improved. Second, if l takes a large integer value, such as $l = K$, a low P_F is achievable but P_D decreases significantly. Third, both the reduction of P_F and the improvement of P_D can be simultaneously achieved by specifying a proper value of l, such as $l = 2$. Forth, an increasing l has little effect on the promotion of P_D, when l is large enough. On the other hand, detector performance is also affected by the oversampling rate K. A large K brings significant promotion to P_D at the expense of an increase in the processing and implementation complexity; we must make a trade-off between the implementation complexity and performance for a practical design.

3.4 Implementation

The block diagram of the proposed detector is shown in Figure 3. The detector composed of three parts: Part (I) is used to obtain the correlation and power for all receiving branches; Part (II) makes the final decision; the branch with maximal power is selected in Part (III). With oversampling, the received sequence is split into multiple detection branches, although the decision for each of the branches can be made by a separate branch-detection block, this is definitely a waste of hardware resource. According to equation (6) and (7), six multiplication operation must be performed for each of the branches to figure out the correlation $R_k(n)$ and the power $P_k(n)$. Moreover, given

$$M_k(n) > \gamma_b \iff |R_k(n)| > P_k(n)\gamma_b \tag{26}$$

the decision $H_k(n)$ can be made by comparing $R_k(n)$ with $P_k(n)\gamma_b$ for the purpose of avoiding the division operation, which has a relatively large hardware resources usage. In other words, $7K$ hardware multipliers must be used to implement all of the K detection branches; this is a waste of hardware resource. For the purpose of reducing the number of multipliers, a scheme where all of the branches share the identical multipliers blocks on a time-division multiplex is introduced in this paper, and the quantity of multipliers is thus reduced from 7*K* to 7.

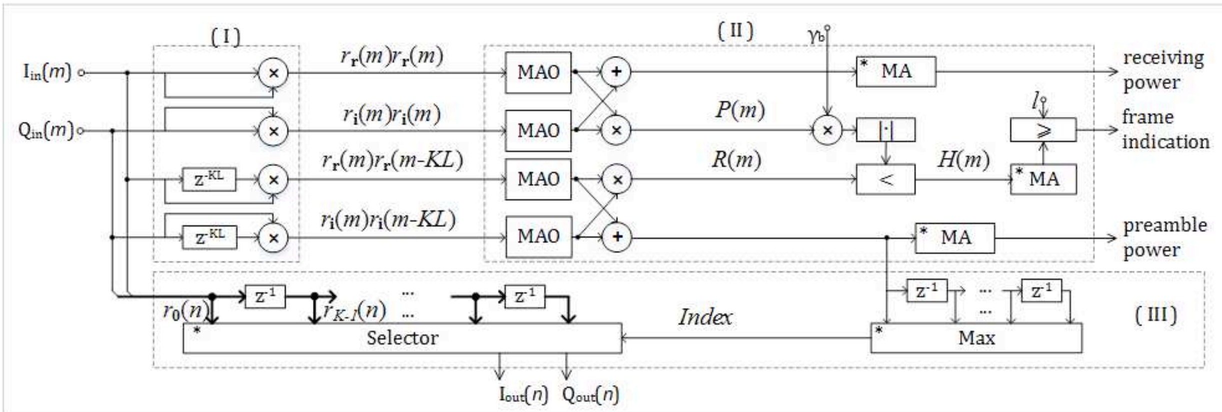


Fig. 3. The Block Diagram for proposed detector, where z^{-x} means that the input samples is delayed by x taps, MAO means the block which splits he input stream into K branches and then moving average each of the branch respectively. The clock frequency for the sub-blocks with " * " at the left-top corner is $f_s = 1/T_s$ and the remaining is Kf_s.

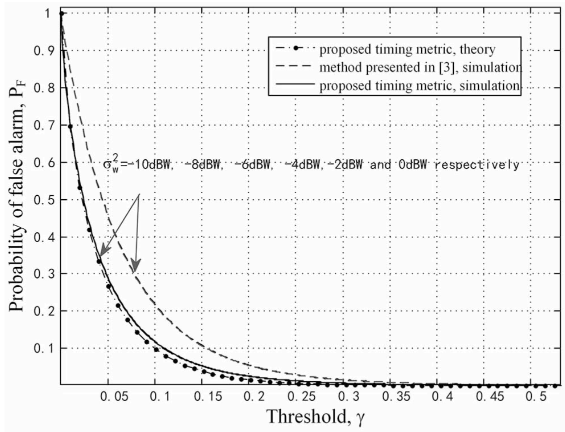
In part (I) of Figure 3, we address the calculation for the correlation $R_k(n)$ and power $P_k(n)$. Because $r_{\mathbf{r}k}(n)r_{\mathbf{r}k}(n-L) = r_\mathbf{r}(nK+k)r_\mathbf{r}(nK+k-KL)$, the product $r_{\mathbf{r}k}(n)r_{\mathbf{r}k}(n-L)$ can be obtained by sampling the product $r_\mathbf{r}(m)r_\mathbf{r}(m-KL)$ at a frequency of f_s. In order to calculate $R_{\mathbf{r}k}(n)$ for all of the K branches, a moving average with oversampling (MAO) block is used, which splits the input stream into K branches, and then performs moving average on each branch. The output of MAO can be expressed as,

$$R_\mathbf{r}(m) = \sum_{n=\lfloor m/K \rfloor - L}^{\lfloor m/K \rfloor} \left(r_\mathbf{r}\left(nK + m\%K\right) r_\mathbf{r}\left(nK + m\%K - KL\right)\right) \quad (27)$$

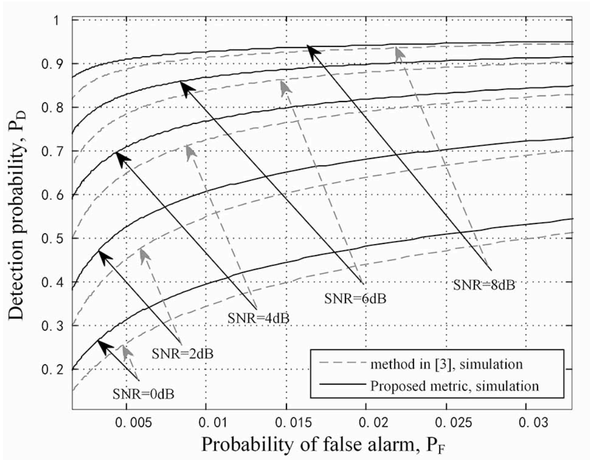
where $\lfloor m/K \rfloor$ means the maximal integer less than m/K, and $m\%K$ means the the remainder of m/K. With the same method, we can find $R_\mathbf{i}(nK+k)$, $P_\mathbf{r}(nK+k)$ and $P_\mathbf{i}(nK+k)$. By time-division multiplexing, the quantity of multipliers can be reduced from 7*K* to 7.

In part (II) of Figure 3, the final decision is obtained by combining all the branch-decisions with the *l*-out-of-*K* rule. Noting that, the decision of the k^{th} branch can be obtained by $H_k(n) = H(nK+k)$, thus the final decision $\hat{H}(n)$ can be made by comparing $\sum_{m=nK}^{nK+K-1} H(m)$ with the predefined integer l according to equation (23). Moreover, according to (8), we also can find the estimations for the average power of the received sequence ($\hat{\sigma}_r(n)$) and its signal components ($\hat{\sigma}_s(n)$), they can be used for automatic gain control and SINR estimation. In part (III) of Figure 3, by comparing the received power $\sigma_{s0}^2(n)$: $\sigma_{s(K-1)}^2(n)$, the index of the branch with the maximal received power can be obtained, and this index is used to decide which of the branches should be output to the follow-up demodulating and decoding processes for the purpose of increasing the received SINR. Since the received sequence is obtained by oversampling at the frequency Kf_s, the period of the STS preamble becomes KL; the input sequence should thus be delayed by KL; this delay operation can be implemented on the FPGA platform by using the on-chip random access memory.

4. Experimental studies



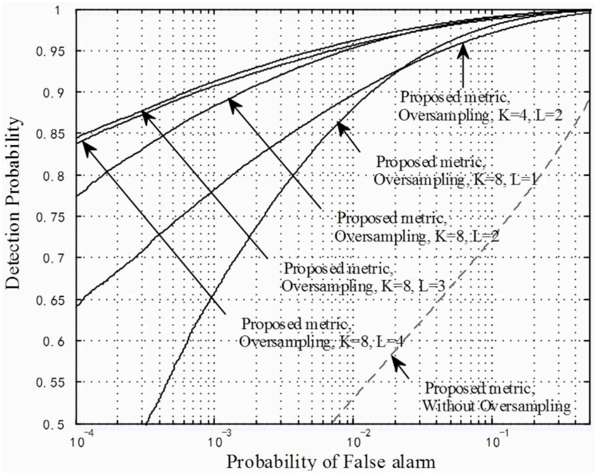
(a) Probability of false alarm of the proposed metric.



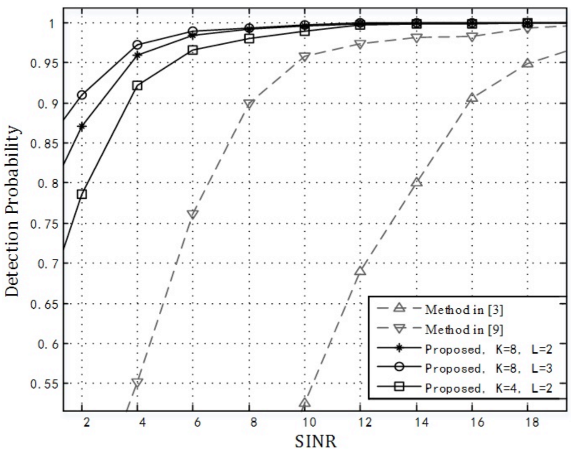
(b) Detection probability of the proposed metric.

Fig. 4. Detection performance of the proposed metric in Rician fading channel, obtained by simulation.

Figure 4 presents the performance of the proposed detection metric, which is obtained by computer simulation. Figure 4(a) shows the relationships between the threshold and the PFA in different noise-and-interference power regimes. We can find that PFA depends only on the threshold γ but not the noise and interference power σ_w^2. In other words, a stable PFA can be achieved by using the proposed detection metric, even if the noise and interference varies frequently. Figure 4(b) presents the detection performance curve of the proposed metric in different SINR regime, where the propagation channel is assumed to be *Rician* fading channel. Simulation results demonstrate that for a given PFA, the proposed detection metric has a higher PD in a low SINR regime compared with the conventional method proposed in [3]. However, in order to achieve a low PFA, the P_D is still too low to satisfy detection demand in vehicular communications, and it must be further improved.



(a) Relationship between P_D and P_F, where SINR = 0dB



(b) P_D in different SINR regimes, where $P_F = 10^{-4}$

Fig. 5. Detection performance with the proposed metric and oversampling schemes in Express way vehicle-to-vehicle communication scenario, where the baseband samples have been processed by an up-sampler with rate K and then filtered by an order-36 Kaiser window before passing through the transmitter ADC.

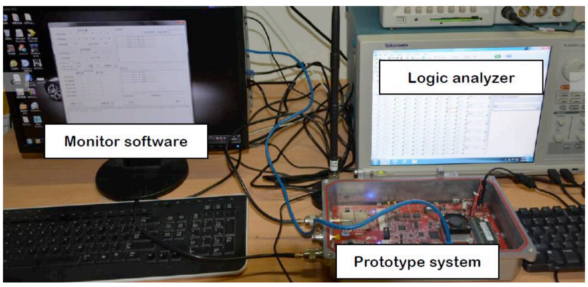


Fig. 6. Prototype of the proposed detector

Taking the influence of non-rectangle BBSF into consideration, detection performance for the proposed detector in express way scenario is shown in Figure 5, where the baseband samples have been processed by an up-sampler with rate 8 and then filtered by an order-36 Kaiser window before passing through the transmitter ADC. The channel model adopted in this paper is presented in [17], which has been accepted as the standard channel model for the IEEE 802.11p standard. Figure 5(a) presents the relationship between P_D and P_F when SINR=0dB, and Figure 5(b) illustrates the detection probability at different SINR regimes when $P_F = 10^{-4}$. Compared with traditional methods and the method utilizing the proposed detection metric alone, P_D is promoted significantly by employing oversampling and the *l*-out-of-*K* rule in a low SINR regime.

Table 1. Resource usage of proposed detector

Resource usage	Proposed method		[3]
	K=4	K=8	
Combinationals	998	763	439
Registers	716	516	205
Memory bits	12,896	6448	1280
9-bit multipliers	14	14	14

In order to demonstrate the complexity and feasibility of the proposed detection method, we implemented it on Xilinx Vertex6 FPGA chip, the prototype is shown in Figure 6. The resource usage of the proposed oversampling-based detector is shown in Table.1. For comparison, we also implemented the method in [3] on the same FPGA. Although more hardware resources is needed to implement our method than that to the traditional method, the improvement of detection performance is remarkable.

5. Conclusions

In this paper, we propose a frame detection method based on improved detection metric and oversampling for the DSRC receiver to manage the special vehicular communication environment. The proposed detection method is evaluated by numerical simulation, and a prototype based on FPGA platform is designed to demonstrate its implementation complexity. The main conclusions are drawn as follow: (1) by using our novel detection metric and oversampling, both high detection probability in a low SINR regime and stable probability of error detection when noise power changes rapidly can be obtained; (2) the reference design based on FPGA device for the detector of the DSRC receiver illustrates that our method achieves a acceptable implementation feasibility and complexity. The proposed method is also applicable to other preamble-aided wireless communication system.

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