

# DATA DETECTION FOR UWB TRANSMITTED REFERENCE SYSTEMS WITH INTER-PULSE INTERFERENCE

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## ABSTRACT

An ultra wideband (UWB) transmitted reference (TR) scheme transmits an un-modulated pulse and a delayed modulated pulse each time. Then a correlation receiver uses the former to demodulate the latter. However, to guarantee satisfactory detection performance in severe multipath distortion, two pulses have to be well separated by at least the channel spread, resulting in reduced data rate. In this paper, the restrictive assumption is relaxed which consequently permits interference from neighboring pulses (termed as inter-pulse interference). Instead of using instantaneous signal from the former pulse as a template, improved estimates by a mean matching technique under different modulation schemes are proposed and used for better detection performance. Besides low complexity approaches, joint maximum likelihood (ML) template estimators and detectors are also proposed. Their statistical performance is analyzed and compared.

## 1. PRELIMINARIES

Ultra-wideband (UWB) communication technology is attractive for different applications [1]. However, mitigation of severe multipath distortion and advanced signal detection is still challenging [2], [3]. An effective transmitted reference (TR) technique, proposed a few decades ago [4], [5], is recently applied to UWB systems with demonstrated demodulation capability in unknown multipath [6]-[9]. The first pulse of each doublet is information free, and the second delayed pulse modulated by binary phase shift keying (BPSK), or pulse amplitude modulation (PAM), or pulse position modulation (PPM) carries user's information. The delay of the second pulse is designed to be larger than the channel spread such that the first pulse does not interfere the second after multipath propagation [8]. Then the former can serve as a template (waveform estimator) to demodulate the latter using a low complexity correlation receiver [6], [8]. However, large pulse spacing inevitably sacrifices data rate for good performance, especially when channel spread is very large [10]. Meanwhile, the first pulse may severely interfere the second, causing inter-pulse interference. Then a conventional TR demodulation technique becomes ineffective because of the very noisy template and low energy capture.

The techniques to be developed will first improve the template (waveform) estimator from which a simple correlation detector can be constructed. Different from [6] and [8] which average signals

within one symbol interval to minimize noise effect but consequently still yield a very "dirty" template, statistical averaging of signals over multiple symbol intervals can purify reference signals contaminated by interference from both information-bearing pulses and background noise. Besides improvement in template estimation, low complexity is achieved by not only easy estimation of the first order statistics, but also feasibility in efficient implementation using analog circuits with basic delay elements and adders due to unique structures of some involved matrices. Additionally, if digital processing is still preferred for high flexibility in signal processing, then digital receivers with mono-bit analog-to-digital converters [11] coupled with the proposed schemes are very promising practical structures for significantly low cost implementation and will be pursued in the future.

The mean based channel estimation idea has been applied to conventional time-hopping impulse radios without transmitting reference signals [3], and pilot symbol assisted modulation that considers a pilot plus noise model [12]. For better performance, a maximum likelihood (ML) criterion to joint detection of inputs and estimation of the waveform is also applied. The mean-square-error (MSE) of each estimator and bit-error-rate (BER) of corresponding detector are provided in close forms. Comparisons among different estimators and detectors are made.

## 2. TRANSMITTED REFERENCE SYSTEMS

A TR UWB system transmits a doublet every  $T_s$  seconds. The second pulse is data modulated by either PAM or PPM and delayed by  $T_d$  seconds. Denote the pulse by  $p(t)$  with duration  $T_p$ . For easy illustration of proposed methods later, we only focus on binary PAM and PPM modulation formats without repetition of a symbol by multiple frames although it is straightforward to generalize models for an arbitrary modulation level and multiple frames.

### 2.1. PAM signal

Denote the binary PAM symbol by  $A_n \in \{\pm 1\}$ . The transmitted signal with power  $P$  can be described by [7]

$$s(t) = \sqrt{P} \sum_n [p(t - nT_s) + A_n p(t - nT_s - T_d)]. \quad (1)$$

Reasonably assume  $T_d > T_p$  and  $T_d + T_p < T_s$ , meaning the first and second pulses do not interfere each other before propagation through a channel. However, it no longer holds at the receiver. If we denote the response of a multipath channel by  $g(t)$  and apply the matched filter  $p(-t)$  first at the receiver, then the received

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signal becomes

$$r(t) = \sum_n [h(t - nT_s) + A_n h(t - nT_s - T_d)] + v(t), \quad (2)$$

where  $h(t) = \sqrt{P}p(t) \star g(t) \star p(-t)$  is the waveform,  $\star$  denotes convolution, and  $v(t)$  represents white Gaussian noise with zero mean and variance  $\sigma_v^2$ . We assume the physical channel is quasi-static, implying it does not change over a transmission burst but will change from burst to burst. Without loss of generality, suppose  $h(t)$  has support in  $(0, T_h)$  and  $T_h + T_d < T_s$  to avoid intersymbol interference (ISI). However, all later discussions can be generalized to a situation with ISI.

In order to derive a compact discrete-time model,  $r(t)$  is sampled every  $T_t$  seconds, related to  $T_d$  by  $T_d = LT_t$  with integer  $L$ . Under such sampling, the number of samples in one symbol interval becomes  $K = \lceil \frac{T_s}{T_t} \rceil$  where  $\lceil \cdot \rceil$  denotes integer ceiling. The maximum multipath channel span is upper bounded by  $q = \lceil \frac{T_h}{T_t} \rceil$  units. Accordingly, all  $q$  channel coefficients are stacked in a vector  $\mathbf{h} = [h_1, \dots, h_q]^T$ . Consider the  $n$ th symbol interval and define discrete-time samples  $r_k = r(t)|_{t=nT_s+kT_t}$  for  $k = 1, \dots, K$ . If all those samples are collected in a vector  $\mathbf{r}_n$ , then

$$\begin{aligned} \mathbf{r}_n &= \begin{bmatrix} \mathbf{h} \\ \mathbf{0}_{(K-q) \times 1} \end{bmatrix} + A_n \begin{bmatrix} \mathbf{0}_{L \times 1} \\ \mathbf{h} \\ \mathbf{0}_{(K-L-q) \times 1} \end{bmatrix} + \mathbf{v}_n \\ &= \mathbf{C}_n \mathbf{h} + \mathbf{v}_n \end{aligned} \quad (3)$$

where  $\mathbf{v}_n$  contains discrete-time noise components,

$$\mathbf{C}_n = \begin{bmatrix} \mathbf{I}_q \\ \mathbf{0}_{(K-q) \times q} \end{bmatrix} + A_n \begin{bmatrix} \mathbf{0}_{L \times q} \\ \mathbf{I}_q \\ \mathbf{0}_{(K-L-q) \times q} \end{bmatrix}, \quad (4)$$

and  $\mathbf{I}_q$  is an identity matrix of dimension  $q$ .

## 2.2. PPM signal

In this system, the second pulse conveys information by the pulse position. Similarly, after propagating through a multipath channel and matched-filtering at the receiver, received signal has the following form [6]

$$\begin{aligned} r(t) &= \sum_n [h(t - nT_s) \\ &+ \sum_{m=0}^1 \delta(I_n - m) h(t - nT_s - T_d - m\Delta)] + v(t) \end{aligned} \quad (5)$$

where  $h(t)$  is the waveform including effects of transmitted pulse, multipath channel and pulse matched filter,  $I_n$  is a binary information sequence taking  $\{0, 1\}$  with equal probability,  $\delta(\cdot)$  is a delta function,  $\Delta$  is the modulation delay. Sampling  $r(t)$  every  $T_t = \frac{1}{L}T_d = \Delta$  seconds yields a vector channel model

$$\mathbf{r}_n = \begin{bmatrix} \mathbf{h} \\ \mathbf{0}_{(K-q) \times 1} \end{bmatrix} + \sum_{m=0}^1 \begin{bmatrix} \mathbf{0}_{(L+m) \times 1} \\ \mathbf{h} \delta(I_n - m) \\ \mathbf{0}_{(K-L-q-m) \times 1} \end{bmatrix} + \mathbf{v}_n. \quad (6)$$

The model (3) or (6) describes a relation of received signal to unknown channel  $\mathbf{h}$  and input. Notice that  $L$  might be much smaller than  $q$ , causing the reference signal (template) to overlap with the desired signal. Our goal is to estimate  $\mathbf{h}$  and detect input as well based on model structures and statistics of input and noise.

## 3. PROPOSED APPROACHES

In order to estimate inputs without knowledge of  $\mathbf{h}$ , one can adopt two different approaches: (a) estimate  $\mathbf{h}$  first and then apply a detection technique such as correlation detection; (b) jointly estimate waveform and detect input. They are described as follows.

### 3.1. Mean based approaches

For low complexity of the estimator, consider the first order statistic of  $\mathbf{r}_n$ .

For the PAM signal, since both  $A_n$  and  $\mathbf{v}_n$  have zero mean, we obtain  $E\{\mathbf{r}_n(1 : q)\} = \mathbf{h}$  where a Matlab notation to extract elements from a vector has been introduced. The mean thus completely captures the channel response, leading to a mean-based estimator based on  $N$  received data vectors

$$\hat{\mathbf{h}} = N^{-1} \sum_{n=1}^N \mathbf{r}_n(1 : q). \quad (7)$$

It is worth mentioning that the above waveform estimation can be implemented in analog circuits by delaying-and-adding signals at different symbol intervals. Properly choose a window size  $N$  for tradeoff between performance and processing delay. To further reduce complexity, an update rule using a forgetting factor  $\mu$  can be applied as follows

$$\hat{\mathbf{h}}_n = (1 - \mu)\hat{\mathbf{h}}_{n-1} + \mu \mathbf{r}_n(1 : q). \quad (8)$$

Once  $\mathbf{h}$  is obtained, an estimate of  $A_n$  can be obtained as

$$\hat{A}_n = \text{sign}(\hat{\mathbf{h}}^T \mathbf{y}_n) \quad (9)$$

according to (3), where

$$\mathbf{y}_n = \mathbf{r}_n(L+1 : L+q) - [h_{L+1}, \dots, h_q, \mathbf{0}_{1 \times L}]^T$$

is the data vector after removing inter pulse interference.

For the PPM signal however,  $E\{\delta(I_n - m)\} = \frac{1}{2}$ . Consider the first  $q$  samples of  $\mathbf{r}_n$

$$\mathbf{r}_n(1 : q) = \mathbf{D}_n \mathbf{h} + \mathbf{v}_{1n}, \quad (10)$$

where matrix  $\mathbf{D}_n = \mathbf{I}_q + \sum_{m=0}^1 \delta(I_n - m) \mathbf{J}^{L+m}$ , matrix  $\mathbf{J}$  of size  $q \times q$  represents a shift-down operator with all elements to be zero except the first lower sub-diagonal to be 1's. Then  $E\{\mathbf{r}_n(1 : q)\} = \mathbf{T} \mathbf{h}$  where  $\mathbf{T} = \mathbf{I}_q + \frac{1}{2} \sum_{j=L}^{L+1} \mathbf{J}^j$ . Therefore,  $\mathbf{h}$  can be estimated by

$$\hat{\mathbf{h}} = N^{-1} \sum_{n=1}^N \mathbf{T}^{-1} \mathbf{r}_n(1 : q). \quad (11)$$

Matrix  $\mathbf{T}$  is a lower triangular matrix. It is thus invertible whose inverse is also lower triangular and has a power series in terms of  $\mathbf{J}$  as  $\mathbf{T}^{-1} = \sum_{j=0}^{q-1} t_j \mathbf{J}^j$ . According to  $\mathbf{T} \mathbf{T}^{-1} = \mathbf{I}_q$ , it can be shown that coefficients  $t_j$ 's satisfy  $t_j + 2^{-1} t_{j-L} + 2^{-1} t_{j-L-1} = 0$  and  $t_0 = 1, t_1 = \dots = t_{L-1} = 0$ . Therefore all  $t_j$ 's can be recursively calculated and stored *a priori* to save computations. In a special case of  $L^2 > q$ , careful derivations show that  $t_{jL+k}$  is a coefficient of the term  $a^k b^{j-k}$  in the expansion of  $(-2)^{-j} (a+b)^j$ . The structure of  $\mathbf{T}^{-1}$  also suggests an efficient implementation of (11) by shifting-and-adding copies of received data vectors at different delays. An adaptive version of this estimator can be similarly developed as before. To detect  $I_n$ , we first obtain data vectors with inter-pulse interference removed

$$\mathbf{y}_{n,m} = \mathbf{r}_n(L+1+m : L+q+m) - [h_{L+1+m}, \dots, h_q, \mathbf{0}_{1 \times (L-m)}]^T$$

for  $m = 0, 1$ . Then according to (6), compare outputs of two correlators and choose the maximum

$$\hat{I}_n = \arg \max_{m \in \{0,1\}} \mathbf{h}^T \mathbf{y}_{n,m}. \quad (12)$$

### 3.2. ML approaches

In [8] and [9], generalized likelihood ratio test (GLRT) detectors and waveform estimators are proposed for TR UWB communication systems. The former adopts the conventional TR modulation scheme and applies GLRT in each symbol interval where the information is repeated multiple frames. The latter considers a model with block transmission of reference signals followed by a block of user's data. Here we apply the ML criterion to a block of data and jointly estimate waveform  $\mathbf{h}$  and  $N$  inputs for data models considered before.

For the PAM signal model (3), joint ML estimation of waveform and inputs can be described as follows

$$(\hat{\mathbf{h}}, \hat{A}_n) = \arg \min_{\mathbf{h}, A_n \in \{\pm 1\}} N^{-1} \sum_{n=1}^N \|\mathbf{r}_n - \mathbf{C}_n \mathbf{h}\|^2. \quad (13)$$

The solution of  $\mathbf{h}$  conditioned on the input sequence is

$$\hat{\mathbf{h}} = \mathbf{B}^{-1} \mathbf{b}, \quad \mathbf{B} = \frac{1}{N} \sum_{n=1}^N \mathbf{C}_n^T \mathbf{C}_n, \quad \mathbf{b} = \frac{1}{N} \sum_{n=1}^N \mathbf{C}_n^T \mathbf{r}_n. \quad (14)$$

For all  $2^N$  possible input sequence candidates, compare costs in (13) with estimated  $\mathbf{h}$  to identify the minimum and subsequently decode inputs. The inverse of  $\mathbf{B}$  requires computational complexity about  $O(q^3)$ . Together with test of  $2^N$  possibilities, corresponding complexity may be prohibitive. However,  $\mathbf{B}$  is structured as follows

$$\mathbf{B} = 2\mathbf{I}_q + N^{-1} \sum_{n=1}^N A_n (\mathbf{J}^L + \mathbf{J}^{-L}) \quad (15)$$

where  $\mathbf{J}^{-1} \triangleq \mathbf{J}^T$  solely for notational convenience although  $\mathbf{J}$  is not invertible. Since  $\mathbf{B}$  is symmetrically banded with bandwidth  $L$  and positive definite with probability one (the main diagonal element is greater than the sum of all other elements on the same row), an existing band Cholesky factorization routine may be applied to significantly save computations. For large  $N$ ,  $\mathbf{B}$  can be approximated by  $\mathbf{B} \approx 2\mathbf{I}_q$  since  $A_n$  has zero mean.

For the PPM signal, joint ML waveform estimation and data detection can be described as

$$(\hat{\mathbf{h}}, \hat{I}_n) = \arg \min_{\mathbf{h}, I_n \in \{0,1\}} N^{-1} \sum_{n=1}^N \|\mathbf{r}_n(1:q) - \mathbf{D}_n \mathbf{h}\|^2. \quad (16)$$

By applying the same approach as in PAM systems, conditional solution of  $\mathbf{h}$  is

$$\hat{\mathbf{h}} = \mathbf{E}^{-1} \mathbf{e}, \quad (17)$$

$$\mathbf{E} = N^{-1} \sum_{n=1}^N \mathbf{D}_n^T \mathbf{D}_n, \quad \mathbf{e} = N^{-1} \sum_{n=1}^N \mathbf{D}_n^T \mathbf{r}_n(1:q). \quad (18)$$

From definition of  $\mathbf{D}_n$ ,  $\mathbf{E}$  has the following structure

$$\mathbf{E} = N^{-1} \sum_{n=1}^N \left[ \mathbf{\Lambda}_n + \sum_{m=0}^1 \delta(I_n - m) (\mathbf{J}^{L+m} + \mathbf{J}^{-L-m}) \right] \quad (19)$$

where  $\mathbf{\Lambda}_n$  is a diagonal matrix

$$\mathbf{\Lambda}_n = \mathbf{I}_q + \sum_{m=0}^1 \delta(I_n - m) \mathbf{J}^{-L-m} \mathbf{J}^{L+m}. \quad (20)$$

The inverse of  $\mathbf{E}$  requires expensive computations. Similarly for large  $N$ ,  $\mathbf{E}$  approaches its expected value by

$$\mathbf{E} \approx \mathbf{I}_q + 2^{-1} \sum_{m=0}^1 (\mathbf{J}^{-L-m} \mathbf{J}^{L+m} + \mathbf{J}^{L+m} + \mathbf{J}^{-L-m}) \triangleq \mathbf{\Phi}.$$

Its inverse can be pre-computed. Approximation results in significantly reduced complexity but only graceful performance degradation for large  $N$ .

## 4. PERFORMANCE STUDY

Given  $N$  received random data vectors  $\mathbf{r}_n$ , our waveform estimators depend on statistics of received signals. Invoking an independent assumption among different inputs and noise, their covariances defined as  $E\{\delta\mathbf{h}\delta\mathbf{h}^T\}$  with  $\delta\mathbf{h} = \hat{\mathbf{h}} - \mathbf{h}$  can be derived in closed forms, which are presented next without detailing derivations due to lack of space.

The mean based waveform estimators for different modulation signals have following covariances

$$\text{COV}_{\text{mean,pam}} = N^{-1} (\mathbf{J}^L \mathbf{h} \mathbf{h}^T \mathbf{J}^{-L} + \sigma_v^2 \mathbf{I}_q), \quad (21)$$

$$\text{COV}_{\text{mean,ppm}} = N^{-1} (\mathbf{W} \mathbf{h} \mathbf{h}^T \mathbf{W}^T + \sigma_v^2 \mathbf{T}^{-1} \mathbf{T}^{-1T}), \quad (22)$$

where  $\mathbf{W} = 2^{-1} \mathbf{T}^{-1} (\mathbf{J}^L - \mathbf{J}^{L+1})$ . Both depend on channel realizations (first terms), channel order, noise power, and data record size  $N$ . The effect of  $q$  is due to estimation of all channel coefficients. However, performance of ML waveform estimators is irrespective of channel realizations, given by

$$\text{COV}_{\text{ml,pam}} = N^{-1} \sigma_v^2 \hat{\mathbf{B}}^{-1} \approx (2N)^{-1} \sigma_v^2 \mathbf{I}_q, \quad (23)$$

$$\text{COV}_{\text{ml,ppm}} = N^{-1} \sigma_v^2 \hat{\mathbf{E}}^{-1} \approx N^{-1} \sigma_v^2 \mathbf{\Phi}^{-1}. \quad (24)$$

Here,  $\hat{\mathbf{B}}$  and  $\hat{\mathbf{E}}$  correspond to input sequences  $\hat{A}_n$  and  $\hat{I}_n$  that minimize (13) and (16) respectively. For large  $N$ , they become independent of input sequences and thus approximations can be made in (23) and (24). Comparison of the trace (denoted by  $tr$ ) of (23) with that of (21) shows that the ML estimator yields smaller MSE than the mean based estimator for PAM signals. For PPM signals, despite infeasible analytical comparison of different estimators, numerical test for a large range of  $q$  (from 2 to 100) and all possible  $L$ 's for given  $q$  shows that  $tr(\mathbf{\Phi}^{-1})$  from (24) is always smaller than trace of the second term in (22), indicating superiority of the ML estimator as well. Although comparisons of the same kind of estimator for PAM and PPM signals are analytically intractable, simulation results show that the MSEs are smaller for PAM signals than for PPM signals.

When waveform  $\mathbf{h}$  is estimated as  $\hat{\mathbf{h}}$ , the bit error rate (BER) for binary PAM signals takes the form [13]

$$\bar{P}_e = E\left\{Q\left(\frac{\mathbf{h}^T \hat{\mathbf{h}}}{\sigma_v \|\hat{\mathbf{h}}\|}\right)\right\}, \quad (25)$$

where  $Q(\cdot)$  is the  $Q$ -function defined as  $Q(x) = \int_x^\infty f(t) dt$ ,  $f(t) = \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}}$ . A closed form for  $\bar{P}_e$  depends on statistics of channel estimate of each kind. Difficulty is encountered to simplify the above expression since random variable  $\hat{\mathbf{h}}$  appears in the lower limit of the integral. Its analytical expression is intractable even though the channel estimator has been derived. Under an assumption of a small error  $\delta\mathbf{h}$  however, after applying Taylor series expansion up to the second order of  $\delta\mathbf{h}$  and using the monotonic decreasing property of the  $Q$ -function, it can be approximated by

$$\bar{P}_e \approx Q(\eta) + \frac{1}{2} \eta f(\eta) \left[ \frac{tr(\text{COV})}{\|\mathbf{h}\|^2} - \frac{\mathbf{h}^T \text{COV} \mathbf{h}}{\|\mathbf{h}\|^4} \right] \quad (26)$$

where  $\eta = \frac{\|\mathbf{h}\|}{\sigma_v}$ , COV is the covariance of each estimator for PAM signals provided before. The first term corresponds to BER with perfect waveform. Imperfect waveform estimation introduces an additional error by the second term.

If PPM is adopted, the BER of a coherent detector is [13]

$$\bar{P}_e = E\left\{Q\left(\frac{\mathbf{h}^T \Psi \hat{\mathbf{h}}}{\sigma_v \|\Psi \hat{\mathbf{h}}\|}\right)\right\}, \quad \Psi = \mathbf{I}_q - \mathbf{J}. \quad (27)$$

Similarly, we can obtain

$$\bar{P}_e \approx Q(\xi) + \xi f(\xi) \text{tr}(\mathbf{\Pi} \text{COV}), \quad (28)$$

where  $\xi = \sqrt{\frac{1-\rho}{2}} \frac{\|\mathbf{h}\|}{\sigma_v}$ ,

$$\mathbf{\Pi} = \frac{\Psi^T \Psi}{4(1-\rho)\|\mathbf{h}\|^2} - \frac{3\Psi^T \Psi \mathbf{h} \mathbf{h}^T \Psi^T \Psi}{8(1-\rho)^2 \|\mathbf{h}\|^4} + \frac{\Psi^T \mathbf{h} \mathbf{h}^T \Psi^T \Psi}{2(1-\rho)^2 \|\mathbf{h}\|^4},$$

$\rho$  is the normalized autocorrelation of waveform at offset  $\Delta$  [13] defined as  $\rho = \sum_{j=1}^{q-1} h_j h_{j+1} \|\mathbf{h}\|^{-2} = \mathbf{h}^T \mathbf{J} \mathbf{h} \|\mathbf{h}\|^{-2}$ , and COV is the covariance of each waveform estimator for PPM signals.

## 5. NUMERICAL STUDY

We adopt normalized second derivative of Gaussian pulse with duration of  $0.7ns$  as transmitted monocycles, set  $T_d = 10ns$ ,  $T_s = 51ns$  and  $\Delta = 0.2ns$ . Multipath channels are generated using the IEEE UWB CM1 channel model with maximum delay spread  $40ns$  and sampled at  $0.1ns$  [10]. About 10% of the multipath energy is beyond  $10ns$ . Channel MSEs versus  $N$  are plotted in Fig. 1 with  $15dB$  signal to noise ratio. The results for mean-based estimation approaches are verified by overlapped analytical curves. Clearly, PAM systems can achieve lower MSEs than PPM systems. ML approaches are superior but are computationally expensive. In Fig. 2, experimental BERs of proposed mean-based detectors with  $N = 200$  are compared with corresponding analytical curves, bounds assuming true channel parameters, and also conventional TR receivers. The proposed detection schemes can improve conventional TR receivers by about  $6dB$  at  $\text{BER} = 10^{-2}$  for both PAM and PPM systems, since inter-pulse interference can be effectively cancelled. With even such a small  $N$ , the experimental results approach their theoretical bounds. Regarding different signaling formats, PAM systems perform only slightly better than PPM systems although channel estimation performance of the former shows clear superiority.

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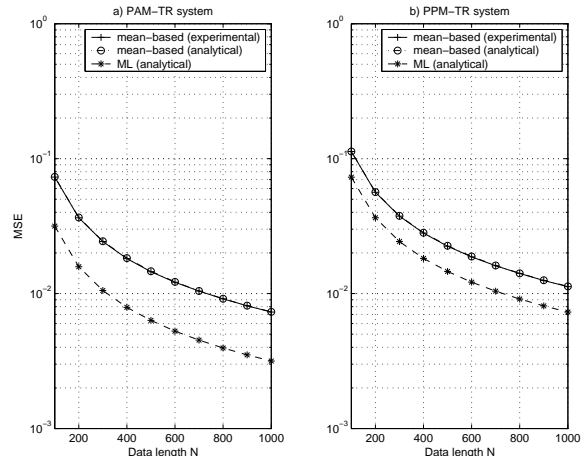


Fig. 1. Channel estimation MSE with respect to data length under  $E_b/N_0 = 15dB$ .

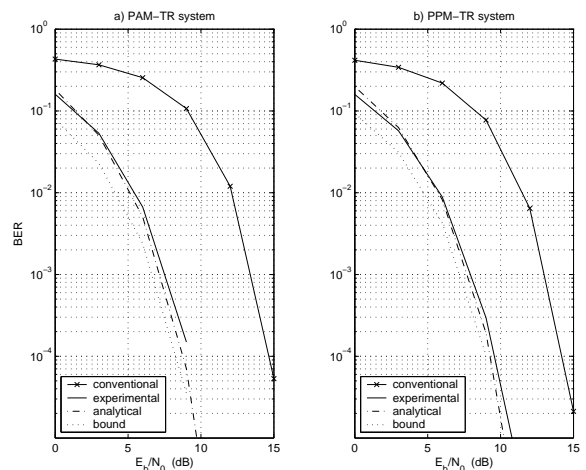


Fig. 2. Comparison of detection performance with conventional TR receiver.

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