Optimum Space-Diversity Receiver for Class A Noise Channels

Carlos L. Giovaneli, Bahram Honary, and Patrick G. Farrell

Department of Communication Systems, Lancaster University
Bailrigg, Lancaster, Lancashire, LA1 4YR, United Kingdom
Tel: +44-1524-593586, Fax: +44-1524-592713
E-mail: c.lopezgiovaneli@lancaster.ac.uk b.honary@lancaster.ac.uk p.g.farrell@lancaster.ac.uk

Abstract

Based on the theory of multiple-sample detection of signal vectors, we propose an optimum space-diversity receiver specifically designed for power-line channels dominated by asynchronous impulsive noise. By simultaneously transmitting the same symbol over two wires and performing two-branch maximal-ratio combining (MRC) at the receiver, the proposed scheme extracts diversity gain without bandwidth expansion. Assuming impulse noise estimation (INE) at the receiver, the new system outperforms the equivalent diversity structure with conventional AWGN detection over the full range of SNR levels. For low values of SNR, *distance gains* in the order of 100 metres can be achieved over the use of single-wire power-line communication systems.

1. Introduction

The use of space-time diversity/coding for data communication over multi-wire power-line channels corrupted by asynchronous impulsive noise was recently proposed in [1], [2]. In [2], two different space-time (ST) receiver structures, i.e., the linear combining (LC) decoder and the repetition-code (RC) decoder, were proposed. Although the LC scheme provides diversity gain, it shows better performance than the RC decoder only at very high signal-to-noise ratio (SNR) levels. On the other hand, the RC scheme does not provide diversity but coding gain, outperforming the LC decoder in the range of low to medium SNR values. Both the LC and the RC decoders employ maximum-likelihood (ML) detection that is optimum in additive white Gaussian noise (AWGN) environments. In this case, the entries of the ST complex noise matrix are assumed to be independent samples of a zero-mean complex Gaussian random process with the same variance. This, however, is not the situation in many power-line communication channels dominated by asynchronous impulsive noise. A basic model for this type of channels is Middleton's ("Class A") noise model [3], where the particular value of the noise variance at each time instant is determined by some source of impulsive noise. Therefore, if we intend to perform multiple-sample detection in both the space and the time domains, a new detection criterion that takes into account the likelihood of unequal noise variances will be needed. In this paper, we provide such criterion and propose an optimal space-diversity receiver for impulse noise channels that outperforms conventional AWGN-based detection schemes over the entire range of SNR values. The emphasis of the paper will centre upon data transmission over 2-wire low-voltage power lines in the presence of Class A impulsive noise.

The remainder of this paper is organised as follows. Section 2 presents Middleton's Class A noise model and a useful simplified version of the Class A model proposed in [4]. In Section 3, we derive the new ML detection criterion for data transmission over Class A noise channels with two spatial dimensions. In Section 4, an optimum two-branch MRC receiver for Class A noise channels is discussed, and the bit error rate (BER) performance of the new scheme with coherent QPSK modulation is compared with both a single-wire transmission system and a two-branch MRC system using conventional AWGN-based ML detection. Some concluding remarks are given in Section 5.

2. Middleton's Impulsive Noise Model

One suitable model for data communications over power lines affected by asynchronous impulsive noise is Middleton's additive white Class A noise (AWCN) channel model [3]. The probability density function (PDF) of the complex Class A noise is represented by a weighted sum of Gaussian probability density functions

$$p_Z(z) = \sum_{m=0}^{\infty} \frac{\alpha_m}{2\pi\sigma_m^2} \exp\left(-\frac{|z|^2}{2\sigma_m^2}\right) \tag{1}$$

with

$$\alpha_m = e^{-A}\frac{A^m}{m!} \tag{2}$$

and complex valued argument z. The variance σ_m^2 is defined as

$$\sigma_m^2 = \sigma^2 \frac{(m/A)+T}{1+T} \tag{3}$$

In (3), the total variance of the Class A noise, σ^2, is the sum of the variance of the Gaussian noise component, σ_G^2, and the variance of the impulsive noise component, σ_I^2. The parameter A is called the *impulsive index* and is defined as the product of the average number of impulses reaching the receiver in the time unit and the mean duration of the impulses. For small A (e.g., A = 0.1), we get highly structured (impulsive) noise whereas for large values of A the noise PDF becomes Gaussian [3]. The parameter T $\left(=\sigma_G^2/\sigma_I^2\right)$ is the Gauss-to-impulse noise power ratio (GIR). The variance σ_m^2 of z is determined by the channel state m (m = 0, 1, 2, 3, …) using equation (3). Since the Class A noise is memoryless, the states are taken independently for every noise sample with probability $P(m,A)=\alpha_m$, which follows a Poisson distribution.

2.1. Simplified class A noise model

The infinite summation of equation (1) can be simplified using the method proposed in [4]. If the impulsive index A is smaller than 0.25, it can be shown that all the terms of m = 3 and higher can be ignored in (1) because their contributions become negligible. Hence a good approximation to the Class A noise PDF is

$$\tilde{p}_Z(z)=\sum_{m=0}^{2}\frac{\alpha_m}{2\pi\sigma_m^2}\exp\left(-\frac{|z|^2}{2\sigma_m^2}\right) \tag{4}$$

Further, we introduce

$$\hat{p}_Z(z)=\max_{m=0,1,2}\left[\frac{\alpha_m}{2\pi\sigma_m^2}\exp\left(-\frac{|z|^2}{2\sigma_m^2}\right)\right] \tag{5}$$

which is the maximum of the three terms of m = 0, 1, and 2. Equation (5) can be written as

$$\hat{p}_Z(z)=\begin{cases}\hat{p}_0(z)=\mathrm{e}^{-A}\cdot\dfrac{1}{2\pi\sigma_0^2}\exp\left(-\dfrac{|z|^2}{2\sigma_0^2}\right), & 0\le|z|<a\\ \hat{p}_1(z)=\mathrm{e}^{-A}\cdot\dfrac{A}{2\pi\sigma_1^2}\exp\left(-\dfrac{|z|^2}{2\sigma_1^2}\right), & a\le|z|<b\\ \hat{p}_2(z)=\mathrm{e}^{-A}\cdot\dfrac{A^2}{4\pi\sigma_2^2}\exp\left(-\dfrac{|z|^2}{2\sigma_2^2}\right), & b\le|z|\end{cases} \tag{6}$$

Variances σ_0^2, σ_1^2 and σ_2^2 are calculated by replacing the appropriate value of m in equation (3), and a, b (>0) are given by

$$\begin{cases}a=\sqrt{\dfrac{2\sigma_0^2\sigma_1^2}{\sigma_0^2-\sigma_1^2}\cdot\ln\left(\dfrac{\sigma_0^2}{\sigma_1^2}A\right)}\\ b=\sqrt{\dfrac{2\sigma_1^2\sigma_2^2}{\sigma_1^2-\sigma_2^2}\cdot\ln\left(\dfrac{\sigma_1^2}{2\sigma_2^2}A\right)}\end{cases} \tag{7}$$

Equation (6) provides a useful approximation that can be conveniently used in impulsive noise estimation (INE) methods.

3. Maximum-Likelihood Detection Criterion for Class A Noise Channels with Two Spatial Dimensions

We consider signalling over 2-wire power-line channels. Assuming isolation between the wires, this system can be viewed as a 2 by 2 multiple-input multiple-output (MIMO) channel with the same number of transmitters and receivers connected by orthogonal parallel sub-channels. So there is no interference between individual sub-channels (power lines with mutual coupling have been considered in [5], where it was shown that the crosstalk interference between wires can be treated as an additional source of random noise). Thus, the complex channel matrix is a diagonal matrix given by

$$\mathbf{H}=\begin{bmatrix}h_{(1,1)} & 0\\ 0 & h_{(2,2)}\end{bmatrix} \tag{8}$$

Throughout this paper we will be focussing on power-line channels with constant matrix elements. In other words, the coefficient $h_{(i,i)}$ (i = 1,2) is the constant path gain from transmitting terminal i to receiving terminal i. Moreover, we shall assume that the complex channel coefficients are normalised so that

$$\sum_{j=1}^{2}\left|h_{(j,j)}\right|^2=2 \tag{9}$$

Physically, this means that we ignore signal attenuations and amplifications in the propagation process.

Spatial multiplexing is applicable to a MIMO channel like the one in (8) to achieve twice the capacity of a single-input single-output (SISO) channel using the same bandwidth and with no additional power expenditure. We note that spatial multiplexing does not provide diversity gain. Alternatively, under equivalent bandwidth and power requirements, it is possible to obtain diversity gain with the capacity (or transmission rate) kept the same for both SISO and MIMO channels. In this paper, we focus our attention on the second alternative. In particular, we consider receive diversity architectures with spatial transmission rate R = 1, which employ simple linear combining methods such as maximal-ratio combining (MRC).

3.1. Multiple-sample detection over class A noise channels

Assuming that the *same* symbol s^i (i = 1, 2, … , M), belonging to a scalar (real or complex) M-ary constellation with M elements and unit average energy, is simultaneously transmitted over the two lines of a 2-wire power-line channel, the received signal vector $\mathbf{r} = [r_1, r_2]^T$, after matched filtering and sampling at the symbol rate, can be written as

$$\mathbf{r} = \sqrt{\frac{E_s}{2}}\mathbf{H}\mathbf{s}^i + \mathbf{n} \quad (10)$$

Here, $\mathbf{s}^i = [s^i, s^i]^T$ is the transmitted symbol vector, $\mathbf{H}$ is the channel matrix (8), and $\mathbf{n} = [n_1, n_2]^T$ is the noise vector. The subscripts denote the corresponding wire number. E_s is the average transmitted symbol energy for SISO channels. Proper normalisation for MIMO channels assumes that the total average transmitted energy per symbol period is constant (E_s) and therefore the symbol energy per transmission wire needs to be reduced by the number of wires ($E_s/2$ in this case). In order to simplify our equations, we will assume from now on that the transmitted symbol vector is already scaled by the factor $\sqrt{E_s/2}$. The components of the noise vector are independent identically distributed (i.i.d.) complex random variables according to Middleton's Class A noise model (1) with (possible) unequal variances. Since the two components of the received signal vector are assumed to be independent samples, we get the following density function conditioned on the symbol vector $\mathbf{s}^i$ and the diagonal channel matrix (8),

$$p(\mathbf{r} \mid \mathbf{s}^i, \mathbf{H}) = \prod_{w=1}^{2} p\left(r_w \mid s^i, h_{(w,w)}\right) \quad (11)$$

Thus, considering the noise PDF given in (5), using equations (8) and (10), and taking into account the possibility of having different channel states in lines 1 and 2, we have

$$p(\mathbf{r} \mid \mathbf{s}^i, \mathbf{H}) = \left(\frac{\exp\left[\frac{-\left| r_1 - h_{(1,1)} s^i \right|^2}{2\left(\sigma_m^2\right)_1} \right]}{2\pi \left(\sigma_m^2\right)_1 / \left(\alpha_m\right)_1} \right) \cdot \left(\frac{\exp\left[\frac{-\left| r_2 - h_{(2,2)} s^i \right|^2}{2\left(\sigma_m^2\right)_2} \right]}{2\pi \left(\sigma_m^2\right)_2 / \left(\alpha_m\right)_2} \right) \quad (12)$$

where $\left(\sigma_m^2\right)_1$ and $\left(\sigma_m^2\right)_2$ represent the Class A noise variances in lines 1 and 2, respectively. The likelihood ratio test for M-ary hypothesis can be written as

$$P(\mathbf{s}^i) p(\mathbf{r} \mid \mathbf{s}^i, \mathbf{H}) > P(\mathbf{s}^j) p(\mathbf{r} \mid \mathbf{s}^j, \mathbf{H}); \quad \forall\ j \neq i \quad (13)$$

We may now use (12) and (13) to define the following likelihood ratio for the optimum decision rule

$$l \equiv \frac{p(\mathbf{r} \mid \mathbf{s}^i, \mathbf{H})}{p(\mathbf{r} \mid \mathbf{s}^j, \mathbf{H})} = \frac{\exp\left[-\frac{\left| r_1 - h_{(1,1)} s^i \right|^2}{2\left(\sigma_m^2\right)_1} - \frac{\left| r_2 - h_{(2,2)} s^i \right|^2}{2\left(\sigma_m^2\right)_2} \right]}{\exp\left[-\frac{\left| r_1 - h_{(1,1)} s^j \right|^2}{2\left(\sigma_m^2\right)_1} - \frac{\left| r_2 - h_{(2,2)} s^j \right|^2}{2\left(\sigma_m^2\right)_2} \right]} > \frac{P(\mathbf{s}^j)}{P(\mathbf{s}^i)} \quad (14)$$

Taking logarithms in both sides of equation (14), and assuming that all the constellation symbols have equal a priori probabilities we arrive at the following maximum likelihood metric

$$\sum_{l=1}^{2} \left(\frac{\left| r_l - h_{(l,l)} s^i \right|^2}{\left(\sigma_m^2\right)_l} \right) < \sum_{l=1}^{2} \left(\frac{\left| r_l - h_{(l,l)} s^j \right|^2}{\left(\sigma_m^2\right)_l} \right), \forall\ j \neq i \quad (15)$$

According to this result, the decision rule for the optimum ML receiver is to select $\hat{s}^i = s^i$ among all the symbols of the modulation constellation if and only if (iif) $\hat{s}^i$ minimises the distance metric (15) for all $j \neq i$. Equation (15) is an example of multiple-sample detection of a signal vector (in the space domain), where the decision rule calls for the *sum* of the received samples (the components of the received vector). In contrast with multi-sample detection in the time or frequency domains, the use of space diversity does not induce any loss in bandwidth efficiency.

4. Optimum Two-Branch Maximal-Ratio Combining Receiver for Class A Noise Channels

In general, the performance of communication systems that employ diversity techniques depends on how multiple signal replicas are combined at the receiver to increase the overall received SNR. Maximal-ratio combining (MRC) is the optimum combining method because the maximum output SNR is equal to the sum of the instantaneous SNRs of the individual signals. MRC has to be used in conjunction with coherent detection, which is the case of equation (15) where both the channel coefficients and the noise variances need to be estimated at the receiver. Defining $U = \left(\sigma_m^2\right)_2 / \left(\sigma_m^2\right)_1$, it turns out that minimising the metric (15) amounts to minimising

$$U\left|r_1 - h_{(1,1)}s\right|^2 + \left|r_2 - h_{(2,2)}s\right|^2 \tag{16}$$

Using (16), we can express receiver equation (10), with the factor $\sqrt{E_s/2}$ omitted and $s^i = s$, as follows

$$\begin{cases} \sqrt{U}r_1 = \sqrt{U}h_{(1,1)}s + \sqrt{U}n_1 \\ \quad r_2 = h_{(2,2)}s + n_2 \end{cases} \tag{17}$$

Multiplying the first equation by $\sqrt{U}h^*_{(1,1)}$, the second equation by $h^*_{(2,2)}$, and summing both results we get

$$\begin{aligned} \tilde{r} &= Uh^*_{(1,1)}r_1 + h^*_{(2,2)}r_2 \\ &= \left(U\left|h_{(1,1)}\right|^2 + \left|h_{(2,2)}\right|^2\right)s + Uh^*_{(1,1)}n_1 + h^*_{(2,2)}n_2 \end{aligned} \tag{18}$$

Substituting (18) in the expansion of (16), it can be shown that the two-branch MRC maximum-likelihood detection rule for AWCN channels is to form the decision variable (18) and decide in favour of s^i, among all the constellation symbols s if

$$s^i = \arg\min_{s\in S} \left|\tilde{r} - s\right|^2 + \left(-1 + U\left|h_{(1,1)}\right|^2 + \left|h_{(2,2)}\right|^2\right)\left|s\right|^2 \tag{19}$$

Equation (18) shows that the parameter U effectively compensates for the effect of the impulsive noise. If $\left(\sigma_m^2\right)_1 > \left(\sigma_m^2\right)_2$, then $U < 1$, and the noise impulse at receiver input 1 is reduced in magnitude. On the other hand, if $\left(\sigma_m^2\right)_1 < \left(\sigma_m^2\right)_2$, then $U > 1$, and the magnitude of the noise component at receiver input 1 is increased in order to *match* the amplitude of the noise impulse in wire 2. The condition $\left(\sigma_m^2\right)_1 = \left(\sigma_m^2\right)_2$, $U = 1$, means that the noise components have the same variance, in which case the detection criterion in (19) becomes identical to the ML metric for AWGN channels.

4.1. Impulse noise estimation (INE)

In order to apply the detection criterion (19), the receiver has to estimate the noise variances during each symbol period T_s. Assuming that the receiver already knows the channel coefficients, the parameters A and T, and the total variance of the Class A noise, σ^2, (see Section 2), it is possible to estimate $\left(\sigma_m^2\right)_1$ and $\left(\sigma_m^2\right)_2$ using approximations (6) and (7). The magnitude of the noise component, $|n_v|$ (v = 1,2) at each receiver input is estimated by performing the following minimisation operation on each branch of the MRC receiver

$$|n|^2 = \arg\min_{s\in S}\left[d^2(r, hs)\right] \tag{20}$$

Here, $d^2(r, hs)$ is the squared Euclidean distance between r and hs, and S is the signal constellation with M elements. The impulse noise estimators (one per branch) calculate the variances σ_0^2, σ_1^2 and σ_2^2, based on the values of A, T, σ^2, and m (= 0, 1, 2), and determine the parameters a and b given by equation (7). After multiplying a and b by the square root of the total variance of the Class A noise, σ^2, the estimated value of $|n|$ is compared against the new limits $\left(a\sqrt{\sigma^2}, b\sqrt{\sigma^2}\right)$ and the estimated value of σ_m^2 is obtained using equation (6). A drawback of this method is that for low values of SNR the minimisation operation in (20) may yield erroneous results when m (the channel state) is greater than zero. Since the probability of occurrence of this event on both lines at the same time is very low, a more efficient scheme to detect and correct a wrong noise estimate in one of the two channels is to use equation (20) to perform hard-decision decoding on the individual signals and then compare the symbol $\hat{s}_1$ detected in line 1 with the symbol $\hat{s}_2$ detected in line 2. Keeping in mind that the same symbol was sent over the two wires, we may use the following algorithm:

(a) IF $\hat{s}_1 = \hat{s}_2$, AND $|n_1| < a\sigma$, AND $|n_2| < a\sigma$: no correction is attempted.

(b) IF $\hat{s}_1 \neq \hat{s}_2$, AND $|n_1|^2 > |n_2|^2$, AND $|n_2| < a\sigma$: use $\hat{s}_2$ to obtain a new estimate of $|n_1|^2$ in branch 1.

(c) IF $\hat{s}_1 \neq \hat{s}_2$, AND $|n_2|^2 > |n_1|^2$, AND $|n_1| < a\sigma$: use $\hat{s}_1$ to obtain a new estimate of $|n_2|^2$ in branch 2.

(d) ELSE: no correction is attempted or an erasure is declared.

Condition (d) represents an unreliable situation where we allow the receiver to make a wrong decision or to have the option of not deciding at all (erasure). By providing erasure flags indicating unreliable (erased) symbols, a powerful outer code can correct those symbols. Figure 1 depicts the proposed two-branch MRC receiver.

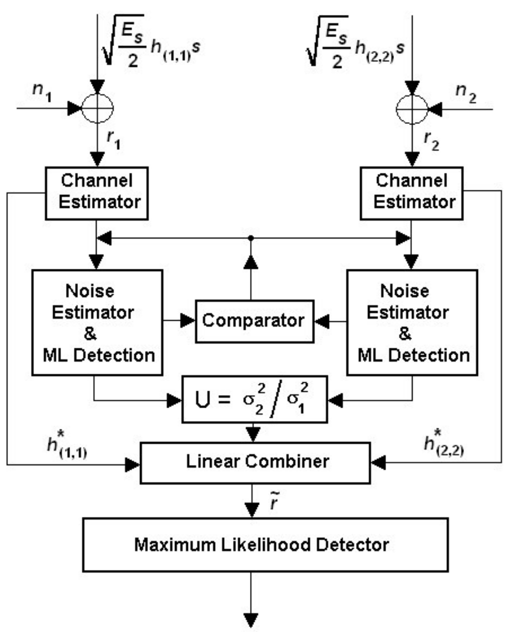

Figure 1. The new two-branch MRC receiver for AWCN channels using noise and channel estimation.

Since the class A noise parameters *A*, *T*, and σ^2 are average quantities, a special sequence of known symbols can be sent prior to or during breaks in actual data transmission to extract the noise components per line and calculate these parameters. From computer simulations, we have found that 1,000 noise samples are sufficient to obtain accurate parameters' estimates.

4.2. Simulation results

Figure 2 shows the BER performance of the proposed system (MRC AWCN) as compared with a single-input single-output (SISO) system (transmission over a single wire) and a two-branch MRC system using conventional AWGN-based ML detection (MRC AWGN). The SISO scheme is also based on AWGN ML detection because only one value per symbol period is possible for the noise variance on a single channel. For comparison we also plot the BER vs. SNR curve for an ideal MRC AWCN system with *perfect* impulsive noise estimation. All the systems use digital QPSK modulation (2 bit/sec/Hz). For simulation purposes, we assume that T_s = 1 second and that the channel bandwidth is 1 Hz. Therefore, E_s is also the transmission power, the noise power spectral density is equal to the noise power, and E_s/N_0 is the same as SNR. Also, the total variance of the Class A noise, σ^2, is normalised to 1/2SNR per complex dimension.

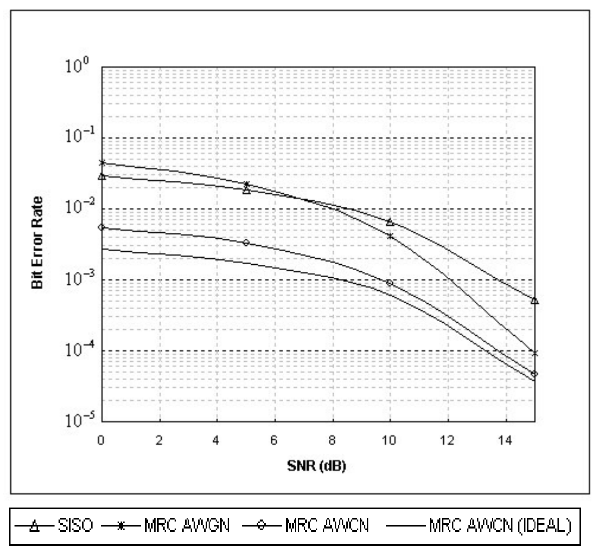

Figure 2. Performance comparison of the proposed two-branch MRC receiver optimised for AWCN channels (MRC AWCN) with a SISO system and a two-branch MRC receiver optimised for AWGN channels. The class A noise parameters are *A* = 0.1 and *T* = -10 dB.

It is seen that the new receiver (MRC AWCN) outperforms both the SISO and the MRC AWGN systems over the entire range of SNR values. At SNR = 5 dB, for example, the new system performs better than the SISO and the MRC AWGN receivers by 6.5 and 5.6 dB, respectively. Comparing the BER vs. SNR curves of the practical MRC AWCN receiver of Figure 1 and the ideal scheme with perfect INE, we see that the latter outperforms the former by 5 dB at SNR = 0 dB, and that this difference decreases for increasing values of SNR. With the exception of the SISO system, the BER performances of all the diversity schemes tend to coincide for SNR values higher than 15 dB.

The importance of working with small values of SNR in class A noise channels comes from the fact that if we were to transmit the same signal over an AWGN channel, we would need an average signal-to-noise ratio given by

$$(\mathrm{SNR})_{av}^{AWGN} = T \times (\mathrm{SNR})_{av}^{AWCN} \quad (21)$$

For example, a system transmitting data over a class A noise channel with T = 0.1 would need 10 times the signal-to-noise ratio required for an AWGN channel!

Another aspect that emphasizes the benefits of designing optimal diversity schemes for data transmission over power-line channels affected by impulsive noise has to do with the attenuation that a signal experiences as it propagates along the power-line wires. Assume, for example, that a power-line communication (PLC) system transmits data over a Class A noise channel with a linear attenuation of 60 dB/Km [6]. The transmitted signal has a power spectral density of –50 dBm/Hz and a bandpass bandwidth of 1 MHz (transmitted power = 10 dBm). Figure 3 shows that if the minimum required received power is -30 dBm (1 μW), a two-branch MRC AWCN scheme offering an SNR improvement of 6 dB over the use of a SISO system will provide this power at a distance of 765 metres from the transmitter. Since the corresponding *minimum-power distance* for the SISO system is 665 metres, it is clear that the MIMO scheme provides a "distance gain" of 100 metres.

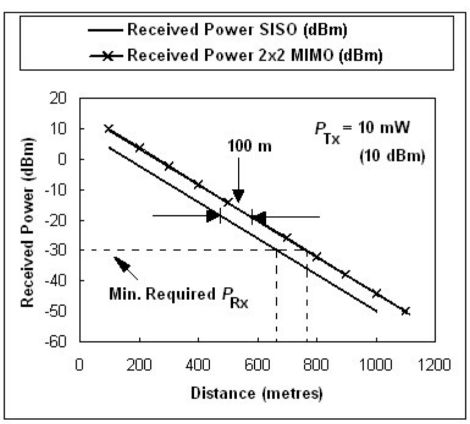

Figure 3. A simple example showing the "distance gain" obtained by optimal power-line diversity schemes.

We note that for short communication links this SNR advantage of the MIMO system implies that we may double the effective transmission distance. Alternatively, we can reduce the transmitted power of the MIMO system and obtain the same received power of the SISO scheme, at the same transmission distance. In the previous example, this amounts to reducing the power delivered by the MIMO transmitter from 10 mW to 2.5 mW.

5. Conclusions

A new maximum-likelihood criterion for multiple-sample detection over two-wire power-line channels corrupted by asynchronous impulsive noise was presented in this paper. Based on this approach, we proposed an optimal two-branch maximal-ratio combining (MRC) receiver and developed an impulsive noise estimation (INE) scheme capable of detecting and correcting a wrong noise estimate in one of the two channels. The results of simulations show that at SNR = 5 dB, the new system outperforms a SISO scheme by 6.5 dB, and a conventional AWGN-based MRC scheme by 5.6 dB. Further work in this subject will be the investigation of INE schemes capable of obtaining more accurate estimates of the class A noise variances.

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