

An Efficient Course Resolution Multiple-Receiver Approach for Reception of Slow Fading Signals in Digital Wireless Communication Systems

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Abstract: Multiple-receiver digital wireless communication systems employ several receivers and a digital central receiver with data fusion to reduce the effect of multipath fading problems. The multiple receiver observations are processed at individual receivers and sent to a digital central receiver. The digital central receiver fuses all the individual receiver data to form global data on which symbol was transmitted. In this study, an efficient course resolution multiple-receiver approach for reception of slow fading signals in digital wireless communication systems is proposed. Each individual receiver observation is represented by course resolution data rather than high resolution data. The proposed approach is investigated for the case of no coherent frequency-shift keying in slow Rayleigh fading and additive Gaussian noise. The performance of the proposed approach is evaluated and compared to that of the optimum low resolution and high resolution approaches. Simulation results indicate that the proposed course resolution approach is efficient and cost effective. The results also indicate that the proposed approach can be used instead of high resolution approach without noticeable performance degradation which highly simplifies the construction and design of the digital wireless communication systems.

Keywords: Multiple Receivers Systems, Multipath Fading, Data Fusion, Course Resolution

Introduction

Multipath fading is caused whenever radio signal arrives at the receiver by more than one path. Characterization of communication channels that have randomly time-variant impulse responses serves as a model for fading digital communication signal transmission over many radio channels such as shortwave ionospheric radio communication (HF), tropospheric scatter (beyond-the horizon) radio communications (UHF and SHF) and ionospheric forward scatter (VHF). The time-variant impulse responses of these channels are due to the constantly changing physical characteristics of the media. Diversity techniques are used to provide replicas of the same data signal transmitted over independently fading channels (Aziz, 2011a; Chen and Tellambura, 2004; Simon and Alouini, 2005; Sendonaris *et al.*, 2007). In this case, the probability that all the signal

components will fade simultaneously is reduced. There are several ways to provide the communication system with n independent fading replicas of the same data-bearing signal. One of the commonly used methods for achieving diversity techniques employs a single transmitting receiver and multiple receiving receivers. Such techniques are expected to increase the system performance compared to a single-receiver system. In the multiple-receiver diversity approach, the j th receiver output, $j = 1, 2, \dots, n$, is a multiple-bit information u_j based only on the observations available at the corresponding receiver. The information from the n communication receivers, u_1, u_2, \dots, u_n , are then combined in a digital receiver using diversity combining to derive a global information. This is equivalent to a decision system with data fusion (Kot and Leung, 2003; Aziz, 2014a; 2014b).

There are three main methods for processing of multipath fading signals in multiple-receiver wireless

communication systems (Viswanathan and Varshney, 1997; Mirjalily *et al.*, 2003; Aziz, 2009a; 2014c). In the first method, the receivers produce samples with enough bits of resolution and the entire system will closely resemble the analog receiver diversity implementations. This method is called high resolution approach. Theoretically, the high resolution processing achieves the optimum performance at the expense of cost and complexity (Hu and Blum, 2002; Blum, 1999; Willett *et al.*, 2000; Aziz, 2013). This case includes the majority research in diversity techniques. However, using course resolution (only a few bits), instead of high resolution, could reduce cost and system complexity considerably. This is the principles of the second and the third methods of multipath fading signal processing. The second method is called course resolution approach where some preliminary processing of observations is carried out at each individual receiver and the results are then sent, using more than one-bit resolution, to the central receiver that combines the received data into final global data. This is not the case for the multiple-receiver diversity systems suggested by most of the published studies (Hu and Blum, 2002; Blum, 1999). The third method is a special case of the second method where only one-bit resolution is used. The problem of one-bit resolution, which is also called low resolution data fusion, has been considered in many literatures (Viswanathan and Varshney, 1997; Mirjalily *et al.*, 2003). The result is a loss of performance in low resolution (one-bit resolution) systems as compared to course resolution (few bits resolution) and high resolution (large number of bits resolution) approaches. Clearly, the advantages of the second and the third methods are reduced cost and complexity.

The optimum solution of multiple-receiver diversity systems in case of course resolution, even for the case of two bits per decision, is very complicated since it requires optimum quantization and the derivatives of the functional relationships between the error rates and the thresholds for all sensors (Kot and Leung, 2003; Viswanathan and Varshney, 1997). Thus the optimum analytical solution is not possible (Wen and Riteey, 1994; Tse *et al.*, 2004; Aziz *et al.*, 2011; 2011b). Some simplified structures based on one bit of quality information in addition to the receiver decisions are developed in the expense of a noticeable lower performance (Mirjalily *et al.*, 2003) and (Wen and Riteey, 1994) for examples). Other simplified structures based on suboptimum objective functions are developed and can be used only in case of two bits per decision (Tse *et al.*, 2004; Chau and Sun, 1996; Shin and Lee, 2008). The purpose of this paper is to introduce a simple, cost effective and efficient course resolution multiple-receiver approach. Unlike the significant contributions reported in the literatures, the proposed approach can easily be applied in case of any number of bits/decision and in case of non-identical sensors. It does not require

analytic expressions for the derivatives of the functional relationships between the error rates and the thresholds for all sensors. The remainder of this paper is organized as follows. The optimum low resolution data fusion in wireless communication systems is briefly reviewed in section 2. Section 3 proposes a course resolution multiple-receiver approach. Section 4 compares the performance of the proposed approach and the low and the high resolution approaches in case of slow Rayleigh fading and additive Gaussian noise. The performance is determined as error rate performance for digital communication systems in fading and noise. Section 5 contains conclusion.

Optimum Low Resolution Data Fusion in Wireless Communication Systems

Since the proposed course resolution approach is based on binary wireless digital communication systems, a quick review of the optimal low resolution data fusion is presented in this section. In case of low resolution wireless communication systems, we are interested in discriminating between two message symbols 0 and 1, encoded as two known waveforms $s_0(t)$ and $s_1(t)$. We suppose that we are to process a received signal $r(t)$ in additive noise $n(t)$. This is a binary hypothesis testing problem with two hypotheses; H_0 designating bit 0 and H_1 designating bit 1, i.e.:

$$\begin{aligned} H_0 : r(t) &= s_0(t) + n(t), \\ H_1 : r(t) &= s_1(t) + n(t) \end{aligned} \quad (1)$$

We assume that there are n local receivers with statistically independent observations r_1, r_2, \dots, r_n and have known probability distributions under both hypotheses $f_R(r_i|s_0)$ and $f_R(r_i|s_1)$, $1, 2, \dots, n$. It is also assumed that the observation at the i^{th} receiver is a scalar r_i . The i^{th} receiver output, $i = 1, 2, \dots, n$, is a binary bit decision u_i based only on the observations available at the corresponding receiver.

For each individual local receiver, the optimum structure should calculate the likelihood ratio and compare it to a likelihood threshold (Sendonaris *et al.*, 2007; Hu and Blum, 2002). The optimal decision rule at each local receiver in case of low resolution can be described as:

$$u_i = \begin{cases} 1, & \text{if } LR_i = \frac{f_R(r_i | s_1)}{f_R(r_i | s_0)} \geq th_i \\ 0, & \text{otherwise,} \end{cases} \quad (2)$$

where, LR_i is the likelihood ratio at the i^{th} receiver and the receiver's threshold, th_i , is depending on the criterion of optimality. When the receiver Signal to

Noise Ratio (SNR) estimates are available and the receiver SNR's change so slowly such that the SNR's estimates can be sent to the central receiver with very high precision, the conditional probability distributions in (2) can be replaced by $f_R(r_i | s_0, \gamma_i)$ and $f_R(r_i | s_1, \gamma_i)$, $i = 1, 2, \dots, n$, where γ_i is the SNR estimate at receiver i (Mirjalily *et al.*, 2003).

The binary decisions from the n communication receivers, u_1, u_2, \dots, u_n , are then sent to a central receiver to derive a global decision \hat{s} on which symbol was transmitted. According to the minimum probability of error rate criterion, the optimal decision combining rule for equally likely message bits (ones and zeros equally likely) is the Maximum Likelihood (ML) decision rule, namely $\hat{s} = 1$ is chosen if (Sendonaris *et al.*, 2007; Aziz, 2014b):

$$\Pr(u_1, u_2, \dots, u_n | s_1) > \Pr(u_1, u_2, \dots, u_n | s_0) \quad (3)$$

The ratio $\frac{\Pr(u_1, u_2, \dots, u_n | s_1)}{\Pr(u_1, u_2, \dots, u_n | s_0)}$ is called the

likelihood ratio of the set of the individual receiver decisions. By assuming the case of independent receiver observations, the optimal decision rule reduces to:

$$\sum_{i=1}^n w_i \begin{matrix} \hat{s} = 1 & > & 0 \\ & < & \\ \hat{s} = 0 & & \end{matrix} \quad (4)$$

where, the coefficients w_i , $i = 1, 2, \dots, n$, are given in terms of the probabilities of correct decision (P_{ci}) and the probabilities of bit error (P_{ei}) as:

$$w_i = \begin{cases} \ln\left(\frac{P_{ci1}}{P_{ei0}}\right), & \text{if } u_i = 1 \\ \ln\left(\frac{P_{ei1}}{P_{ci0}}\right), & \text{if } u_i = 0, i = 1, 2, \dots, n \end{cases} \quad (5)$$

$$\begin{aligned} P_{ci1} &= \Pr(u_i = k | s_k), \\ P_{ei0} &= \Pr(u_i = 1 - k | s_k), k = 0, 1 \end{aligned} \quad (6)$$

The optimum fusion rule of the course resolution approach (4) is interpreted as the sum of the reliabilities of the receiver decisions. The final global decision of the digital central receiver is based on the sign of this sum.

Proposed Course Resolution Multiple-Receiver Approach

Consider a multipath fading environment where noncoherent binary Frequency-Shift Keying (FSK) is to

be employed. In this case, n individual receivers, each with its own receiver, are employed to achieve a diversity gain (Simon and Alouini, 2005; Hu and Blum, 2002; Willett *et al.*, 2000). Each individual receiver employs the structure of the standard single-receiver noncoherent FSK receiver whose implementation is well known (Aziz, 2014c; Tse *et al.*, 2004; Chau and Sun, 1996). Each of the n individual receivers consists of two bandpass filters, each operated at a sinusoid with a different frequency (ω_0 or ω_1). As shown in Fig. 1, the bandpass filters are operated at the sinusoid frequencies over the data period (bit interval). Frequency ω_1 corresponds to a "1" being sent, while frequency ω_0 corresponds to a "0" being sent. The outputs of the two bandpass filters are envelope detected and then sampled at the end of the bit period. The samples outputs from the two envelope detectors are the random variables R_{0j} and R_{1j} , which are the outputs of the j th individual receiver. The data at each individual receiver is obtained by observing the value $R_{1j} - R_{0j}$. The important value of the random variable $V_j = R_{1j} - R_{0j}$ is denoted by v_j . The j th - sensor decision will be based on v_j and on the signal-to-noise (SNR) estimate (if it is available). Let Γ_j be a random variable which denotes the SNR estimate at sensor j and let γ_j denotes the samples of this random variable. The time-varying responses that occur and the characterization of the communication fading channels are treated in statistical terms (Shin and Lee, 2008). There are several probability distributions that can be considered in attempting to model the statistical characteristics of the fading channel. In case of large number of scatters in the channel, as the case in ionospheric or tropospheric signal propagation, central limit theorem leads to a Gaussian process model for the channel impulse response. If the process has zero mean, then the envelope of the channel response at any time instant has a Rayleigh probability distribution and the phase is uniformly distributed in the interval $(0, \pi_2)$ (Simon and Alouini, 2005; Kot and Leung, 2003).

In this study, slow Rayleigh fading is considered. The observations at each receiver are assumed to include additive zero-mean Gaussian noise. The fading and noise are assumed to be independent from receiver to receiver. In order to obtain signals that fade independently, certain separation is required between any two receivers (Simon and Alouini, 2005; Blum, 1999). Thus the multiple receivers must be spaced sufficiently far apart that the multipath components in the signal have significantly different propagation delays at the receivers. The two main steps for developing the proposed course resolution multiple-receiver approach are (1) obtaining the individual receiver likelihood ratios and (2) deriving the combining fusion rule of the digital central receiver.

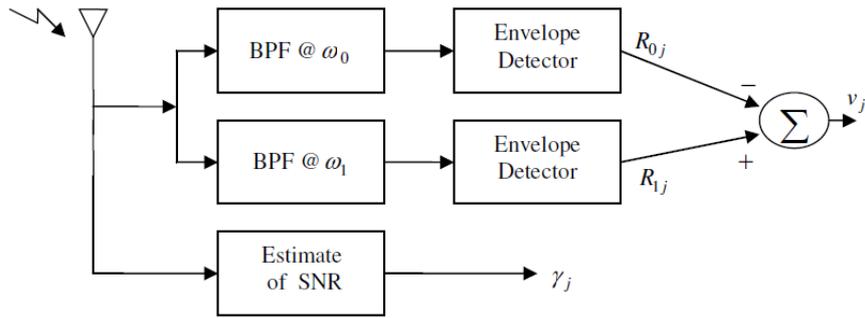


Fig. 1. Block diagram of each individual receiver in case of noncoherent FSK

Obtaining the Individual Receiver Likelihood Ratios

Since the optimum decision approach of the *j*th individual receiver should perform a mapping of its likelihood ratio, which is a function of V_j and Γ_j then the value of u_j will depend on the likelihood ratio. By assuming that the marginal Probability Density Function (PDF) of each receiver SNR is the same under either hypothesis, we can write:

$$\ln \frac{f_{V_j, \Gamma_j}(v_j, \gamma_j | 1sent)}{f_{V_j, \Gamma_j}(v_j, \gamma_j | 0sent)} = \ln \frac{f_{V_j}(v_j | 1sent, \gamma_j)}{f_{V_j}(v_j | 0sent, \gamma_j)} \quad (7)$$

where, $f_{V_j, \Gamma_j}(v_j, \gamma_j | s sent)$ is the joint pdf of V_j and Γ_j given that s was sent ($s = 0$ or 1). The proposed method allows the *j*th receiver to take on one of L values instead of only two values. This can be done by mapping the *j*th likelihood ratio, which is a function of V_j and Γ_j , using B number of bits ($L = 2^B$). Thus the *j*th receiver decides $u_i = k$ if $(v_j, \gamma_j) \in A_{j,k}$, where:

$$A_{j,k} = \left\{ (v_j, \gamma_j) : t_{j,k-1} \leq \ln \left(\frac{f_{V_j}(v_j | 1sent, \gamma_j)}{f_{V_j}(v_j | 0sent, \gamma_j)} \right) < t_{j,k} \right\} \quad (8)$$

For a given receiver threshold t_j , if $\ln \left(\frac{f_{V_j}(v_j | 1sent, \gamma_j)}{f_{V_j}(v_j | 0sent, \gamma_j)} \right)$ is low (or high) enough, the *j*th receiver decision will take the value 0 (or 1) with high probability level and vice versa. We perform this mapping using the following relations:

$$u_j = 2 \left[\frac{\ln \left(\frac{f_{V_j}(v_j | 1sent, \gamma_j)}{f_{V_j}(v_j | 0sent, \gamma_j)} \right) - t_{\min}}{t_{\max} - t_{\min}} \right]^2; \quad (9a)$$

if $t_{\min} \leq \ln \left(\frac{f_{V_j}(v_j | 1sent, \gamma_j)}{f_{V_j}(v_j | 0sent, \gamma_j)} \right) \leq t_j$

$$u_j = 1 - 2 \left[\frac{\ln \left(\frac{f_{V_j}(v_j | 1sent, \gamma_j)}{f_{V_j}(v_j | 0sent, \gamma_j)} \right) - t_{\min}}{t_{\max} - t_{\min}} \right]^2; \quad (9b)$$

if $t_j \leq \ln \left(\frac{f_{V_j}(v_j | 1sent, \gamma_j)}{f_{V_j}(v_j | 0sent, \gamma_j)} \right) \leq t_{\max}$

By this way we ensure that the value of the receiver decision is gradually varies from zero to one according to the difference between the likelihood

ratio $\ln \left(\frac{f_{V_j}(v_j | 1sent, \gamma_j)}{f_{V_j}(v_j | 0sent, \gamma_j)} \right)$ and the receiver threshold t_j .

The issue of optimum mapping between the likelihood ratio and the receiver decision is not considered here, but simply a uniform mapping is assumed, which is very simple. Thus the values of the receiver decisions in the intervals $[0, 1]$ are divided into L uniform step size levels, with $1/L$ step size value. If the value of the receiver decision falls within the *k*th interval ($k = 1, 2, \dots, L$), then the mapped value is taken to be the midpoint of that interval.

Deriving the Combining Fusion Rule of the Digital Central Receiver

The minimum probability of error (optimum) approach for the central receiver to fuse the individual receiver data is to form the likelihood ratio. If the data in the digital communication channel is equally likely, then the central receiver threshold will be zero. In this case, the global decision for the central receiver is (assuming independent receiver's decisions):

$$u_g = \begin{cases} 1 & \text{if } \ln \frac{\text{Prob}(u_1, u_2, \dots, u_n | 1sent)}{\text{Prob}(u_1, u_2, \dots, u_n | 0sent)} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

where, the required probabilities in (10) can be evaluated as:

$$\frac{\text{Prob}(u_1, u_2, \dots, u_n | 1sent)}{\text{Prob}(u_1, u_2, \dots, u_n | 0sent)} = \prod_{j=1}^n \frac{\text{Prob}(u_j | 1sent)}{\text{Prob}(u_j | 0sent)} \quad (11)$$

If we assume that n_0 receivers decide 0, n_1 receivers decide u_{j1} , n_2 receivers decide u_{j2}, \dots, n_L receivers decide u_{jL} and n_+ receivers decide 1, then (11) can be rewritten as:

$$\prod_{j=1}^n \frac{\text{Prob}(u_j | 1sent)}{\text{Prob}(u_j | 0sent)} = \prod_{j=1}^{n_0} \frac{\text{Prob}(u_j = 0 | 1sent)}{\text{Prob}(u_j = 0 | 0sent)} \dots \prod_{j=1}^{n_1} \frac{\text{Prob}(u_j = u_{j1} | 1sent)}{\text{Prob}(u_j = u_{j1} | 0sent)} \prod_{j=1}^{n_2} \frac{\text{Prob}(u_j = 1 | 1sent)}{\text{Prob}(u_j = 1 | 0sent)} \quad (12)$$

Taking the natural logarithm (monotonic increasing function) of (12) leads to:

$$\ln \left(\prod_{j=1}^n \frac{\text{Prob}(u_j | 1sent)}{\text{Prob}(u_j | 0sent)} \right) = \sum_{j=1}^{n_0} \ln \left(\frac{\text{Prob}(u_j = 0 | 1sent)}{\text{Prob}(u_j = 0 | 0sent)} \right) + \dots + \sum_{j=1}^{n_+} \ln \left(\frac{\text{Prob}(u_j = 1 | 1sent)}{\text{Prob}(u_j = 1 | 0sent)} \right) \quad (13)$$

Where:

$$\text{Prob}(u_j = 0 | sent) = \int_0^{t_{\min}} f_{v_j}(v_j | sent) dv_j, j = 1, 2, \dots, n_0, s = 0, 1 \quad (14a)$$

$$\text{Prob}(u_j = u_{jk} | sent) = \int_{t^{(k-1)}}^{t_k} f_{v_j}(v_j | sent) dv_j, k = 1, 2, \dots, L, j = 1 : (n_1 + \dots + n_L), s = 0, 1 \quad (14b)$$

$$\text{Prob}(u_j = 1 | sent) = \int_{t_{\max}}^{\infty} f_{v_j}(v_j | sent) dv_j, j = 1, 2, \dots, n_+, s = 0, 1 \quad (14c)$$

When estimates of the receiver SNR's are available, the probability terms in (14) can be evaluated in terms of the probability density function of the SNR as:

$$\text{Prob}(u_j = u_{jk} | sent) = \int_{(v_j, \gamma_j) \in A_{j,k}} f_{v_j}(v_j | sent, \gamma_j) dv_j, d\gamma_j, j = 1 : n, k = 1 : L, s = 0, 1 \quad (15)$$

From (4) and (7), the decision rule for the central receiver can be rewritten as:

$$u_g = \begin{cases} \left(\sum_{j=1}^{n_0} (u_j = 0) w_{j0} + \sum_{j=1}^{n_1 + \dots + n_L} \sum_{k=1}^L I(u_j = u_{jk}) W_{jk} + \sum_{j=1}^{n_+} I(u_j = 1) W_{j1} \right) > 0 \\ 0; & \text{otherwise,} \end{cases} \quad (16)$$

Where:

$$W_{jk} = \left\{ \ln \left(\frac{\text{prob}(u_j = c | 1sent)}{\text{prob}(u_j = c | 0sent)} \right) \right\}, k = 1, 2, \dots, L, c = 0, 1, u_{jk} \quad (17)$$

and $I(u_j = h)$ is an indicator function which is unity if $u_j = h$ and zero otherwise. From (15) and (17) and by taking into consideration the percentage of the confidence levels for each receiver decision, we can write:

$$W_{jk} = \begin{cases} \ln \left(\frac{\int_{(v_j, \gamma_j) \in A_{j,0}} f\Gamma_j(\gamma_j) f_{v_j}(v_j | 1sent, \gamma_j) dv_j d\gamma_j}{\int_{(v_j, \gamma_j) \in A_{j,k}} f\Gamma_j(\gamma_j) f_{v_j}(v_j | 0sent, \gamma_j) dv_j d\gamma_j} \right) & \text{if } u_j = 0, j = 1, 2, \dots, n_0 \\ \ln \left(u_j \frac{\int_{(v_j, \gamma_j) \in A_{j,k}} f\Gamma_j(\gamma_j) f_{v_j}(v_j | 1sent, \gamma_j) dv_j d\gamma_j}{\int_{(v_j, \gamma_j) \in A_{j,k}} f\Gamma_j(\gamma_j) f_{v_j}(v_j | 0sent, \gamma_j) dv_j d\gamma_j} \right); & \text{if } u_j = u_{jk}, k = 1, 2, \dots, (L/2) \\ \ln \left((1-u_j) \frac{\int_{(v_j, \gamma_j) \in A_{j,k}} f\Gamma_j(\gamma_j) f_{v_j}(v_j | 1sent, \gamma_j) dv_j d\gamma_j}{\int_{(v_j, \gamma_j) \in A_{j,k}} f\Gamma_j(\gamma_j) f_{v_j}(v_j | 0sent, \gamma_j) dv_j d\gamma_j} \right); & \text{if } u_j = u_{jk}, k = (L/2 + 1) : L \\ \ln \left(\frac{\int_{(v_j, \gamma_j) \in A_{j,1}} f\Gamma_j(\gamma_j) f_{v_j}(v_j | 1sent, \gamma_j) dv_j d\gamma_j}{\int_{(v_j, \gamma_j) \in A_{j,1}} f\Gamma_j(\gamma_j) f_{v_j}(v_j | 0sent, \gamma_j) dv_j d\gamma_j} \right); & \text{if } u_j = 1, j = 1, 2, \dots, n_+ \end{cases} \quad (18)$$

Performance Comparison

The performance is evaluated in terms of error rate in case of noncoherent FSK in slow Rayleigh fading and additive Gaussian noise. The probability of error of the central receiver is:

$$P_e = \text{prob}(0 sent) \text{prob}(error | 1sent) + \text{prob}(1sent) \text{prob}(error | 1sent) \quad (19)$$

Where:

$$\text{prob}(error | 0 sent) = \sum_{u_1=0, u_{j1}, u_{j2}, \dots, 1} \dots \sum_{u_n=0, u_{n1}, u_{n2}, \dots, 1} \text{prob}(u_g = 1 | u_1, \dots, u_n) \times \text{prob}(u_1 | 1sent) \dots \text{prob}(u_n | 0sent) \quad (20)$$

and Prob ($u_g = 1 | u_1, \dots, u_n$) is determined using the central receiver fusion rule (10). Similar equation exists for Prob (error | 1 sent). In case of slow Rayleigh fading, the probability density function of the signal-to-noise ratio at the j th receiver, $f_{\Gamma_j}(\gamma_j)$, will be (Blum, 1999; ElAyadi *et al.*, 1996; Aziz, 2011c; 2009b; 1997):

$$f_{\Gamma_j}(\gamma_j) = \frac{1}{\mu_j} \exp\left(-\frac{\gamma_j}{\mu_j}\right) U(\gamma_j) \quad (21)$$

where, μ_j is the average signal-to-noise ratio at the j th receiver and:

$$U(x) = \begin{cases} 1; & \text{if } x \geq 0 \\ 0; & \text{otherwise} \end{cases} \quad (22)$$

Using limiting argument and assuming that the two bandpass filters at each receiver have non overlapping passband which are sufficiently separated, we can deduce $f_{v_j}(v_j|0 \text{ sent}, \gamma_j)$ and $f_{v_j}(v_j|1 \text{ sent}, \gamma_j)$ as in (Blum, 1999; Willett *et al.*, 2000; Aziz, 1999; Aziz *et al.*, 1997).

To simplify matters, we assume the case of identical receivers (same receiver thresholds). We also assume that an accurate estimate of the signal-to-noise ratio of the observations is available at each individual receiver and the estimate is equal to the true SNR. The actual values of the minimum and maximum thresholds depend on the expected noise range. The noise range is taken to be 3σ , where σ^2 is the average power of the noise. Figure 2 shows a plot of the probability of error versus SNR for different values of number of receivers, assuming two bits for each receiver decision ($B = 2$). The global performance improvement as the number of receivers increases is obvious. Figure 3 compares the global performance of the optimum low resolution approach and the proposed course resolution approach as well as the optimum high resolution approach in case of fifteen identical sensors ($n = 15$) for different SNR. The degradation in the performance of the optimum low resolution approach compared to the proposed course resolution and the optimum high resolution approaches is obvious. It is clear from Fig. 3 that the global performance of the optimum high resolution approach is much better than the performance of the optimum low resolution approach for the same SNR. The global performance improvement of the proposed approach with $B = 2$ is significant. The increment in the global performance improvement in case of the proposed approach decreases as the number of bits per decision increases. The performance of the proposed approach with two or three bits per decision is much better than the performance of the optimum low resolution approach. The performance of the proposed approach with three bits per decision ($B = 3$) is reasonably close to

the performance of the optimum high resolution approach. Figure 4 shows the same plots, as in Fig. 3, in case of twenty five identical sensors ($n = 25$) for different SNR. It is clear from Fig. 4 that the previous results are also valid. Since the proposed approach achieves a reasonable performance, compared to the performance of the optimum high resolution approach, with few numbers of bits, it reduces cost and complexity of receiver designs considerably.

Figure 5-7 show the plots of the probability of error of the proposed course resolution diversity approach versus SNR for different values of number of bits per receiver decision (B) assuming a fixed value of number of receivers (n). Figure 5 shows the plot of the probability of error versus SNR for $B = 1, 2, 3, 4$ and 5 , assuming ten receivers ($n = 10$). It is clear from Fig. 5 that the error probability decreases as the number of bits per decision increases. As shown in Fig. 5, there is a significant improvement in the global performance when B increases from 1 to 2 or from 2 to 3. The global performance improvement is insignificant when $B = 4$ or 5 . Figure 6 and 7 show the same plots, as in Fig. 5, in case of sixteen ($n = 16$) and twenty two ($n = 22$) receivers, respectively. From Fig. 5-7, it is clear that using three or four bits per decision may be most appropriate. It is impractical to use more than three or four bits per decision to avoid additional hardware cost without significant performance improvement.

The performance of the proposed soft approach is compared to the performance of the course resolution with quality information approach presented in (Thomopoulos *et al.*, 1987) where the local receivers send one or more quality bit information in addition to the individual receiver binary decisions ((Thomopoulos *et al.*, 1987) for the details). The performance of the proposed soft approach is also compared to the performance of the optimum course resolution approach (highest performance) presented in (Lee and Chao, 1989) where the optimum partitioning is derived using the maximum distance criterion ((Lee and Chao, 1989) for the details). The results are shown in Fig. 8 and 9 for the same numbers of bits per decisions B . Figure 8 compare the performances assuming that $n = 12$ and $B = 2$ and Fig. 9 shows the same plots assuming that $n = 17$ and $B = 3$.

It is clear from Fig. 8 and 9 that the proposed course resolution approach outperforms the course resolution with quality information approach (Thomopoulos *et al.*, 1987) for the same number of bits. Unlike the course resolution with quality information approach, the proposed course resolution approach can be applied easily to non-identical receivers and can be extended easily to any number of bits. Figure 8 and 9 also show that the optimum course resolution approach (Lee and Chao, 1989) has a little performance improvement over the proposed course resolution approach for the same number of bits.

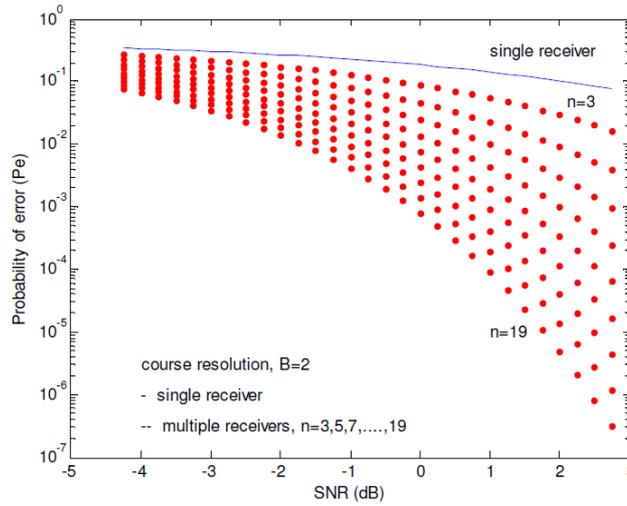


Fig. 2. Error rate performance versus SNR for different values of number of receivers (n)

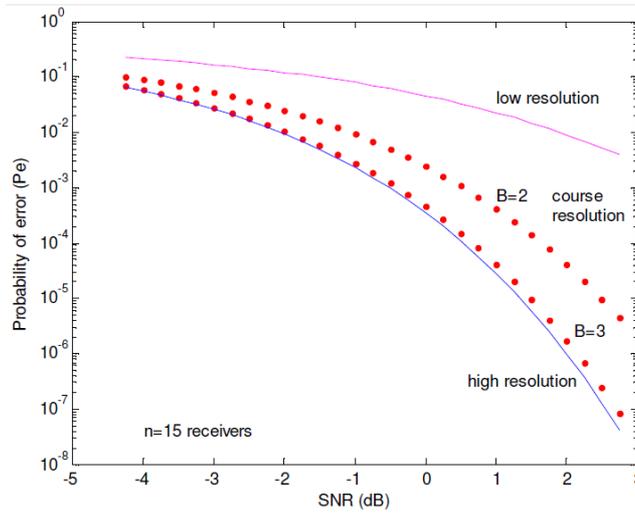


Fig. 3. Comparison of low, course and high resolution error rate performance, $n = 15$

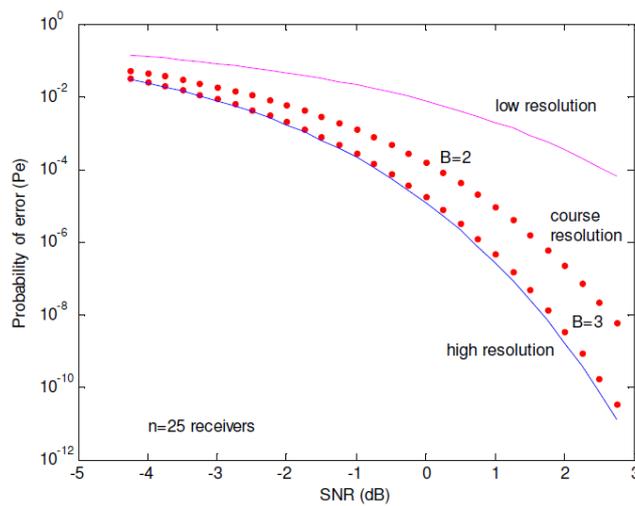


Fig. 4. Comparison of low, course and high resolution error rate performance, $n = 25$

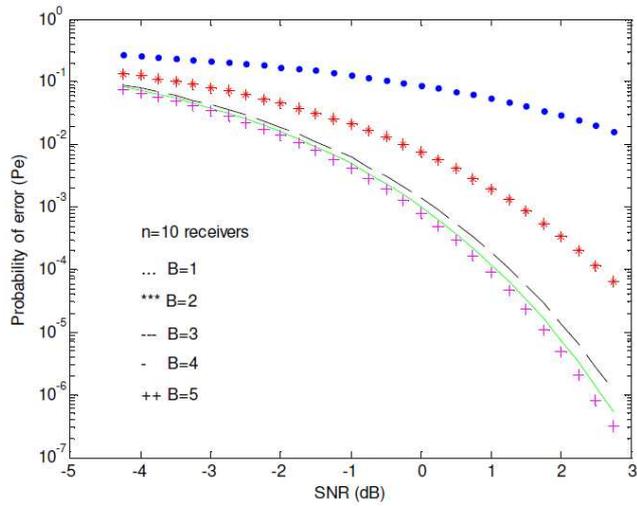


Fig. 5. Comparison of the proposed approach error rate performance for different values of number of bits per receiver decision (B), $n = 10$

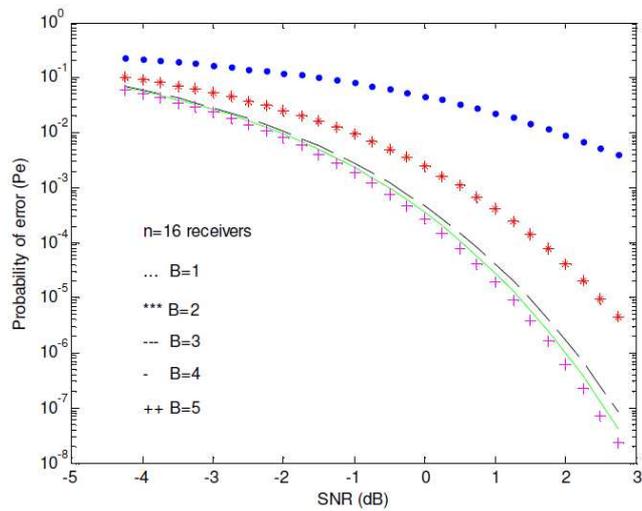


Fig. 6. Comparison of the proposed approach error rate performance for different values of number of bits per receiver decision (B), $n = 16$

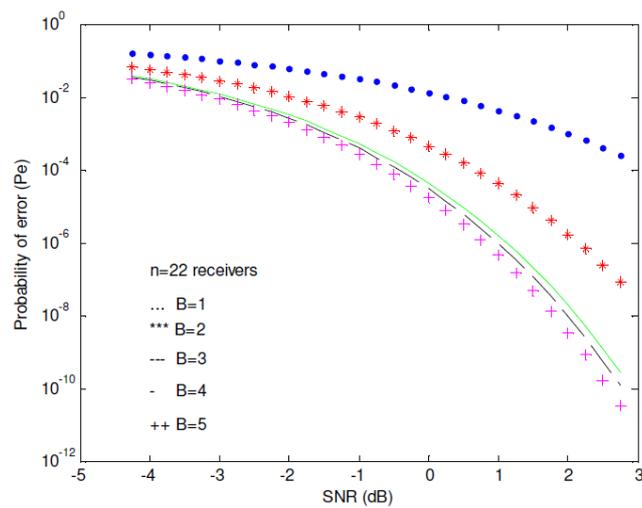


Fig. 7. Comparison of the proposed approach error rate performance for different values of number of bits per receiver decision (B), $n = 22$

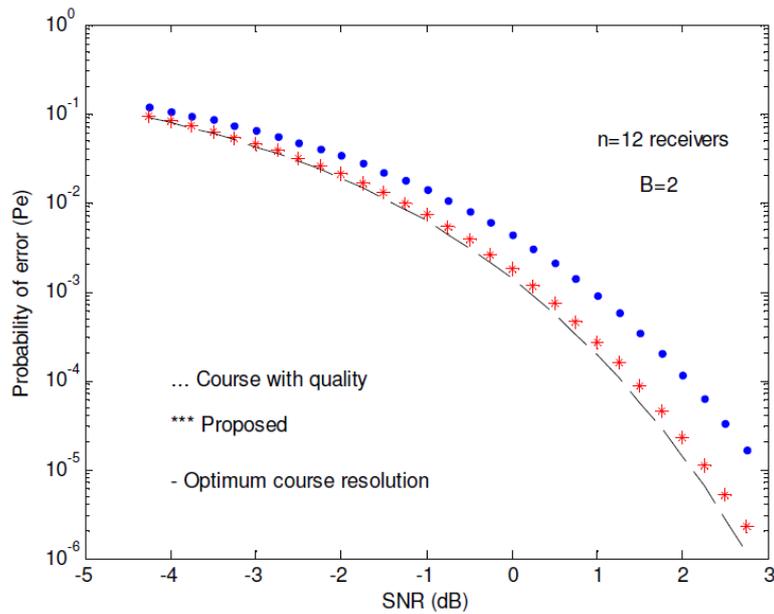


Fig. 8. Comparison of the proposed approach, course resolution with quality information approach and the optimum course resolution approach for $n = 12$ and $B = 2$

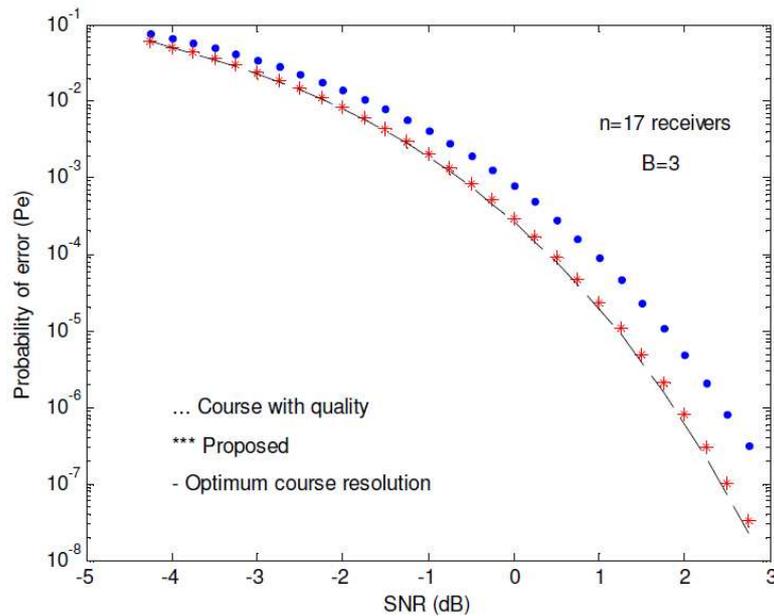


Fig. 9. Comparison of the proposed approach, course resolution with quality information approach and the optimum course resolution approach for $n = 17$ and $B = 3$

However, unlike the optimum course resolution approach, which requires the derivatives of the functional relationships between the individual receiver error probabilities and the individual receiver thresholds, the proposed course resolution approach does not require these relationships. It is also clear from Fig. 8 and 9 that the performance improvement of the optimum course resolution approach over the proposed course resolution

approach decreases as the number of receivers and the number of bits per decisions increase.

Compared to other course resolution approaches, the novelty of the proposed course resolution approach is that each receiver generates a course decision value between 0 and 1 according to the difference between the receiver's likelihood ratio and the receiver's threshold. Each receiver's course decision represents its

degree of reliability on that decision. Unlike the published course resolution approaches, the combining rule of the proposed course resolution approach fuses reliability terms weighted by confidence levels to derive the decision of the central receiver. From the previous examples, it is clear that the proposed course resolution approach is very efficient. In addition, the proposed course resolution approach has the following advantages: (1) it can be applied easily to any number of non-identical and identical receivers, (2) it can be extended easily to any number of bits, (3) it can be applied easily to any type of distributed observations, (4) does not require the derivatives of the functional relationships between the individual receiver error probabilities and the individual receiver thresholds and (5) the computations do not grow exponentially either as the number of bits or the number of sensors increases. The results of these advantages are the reduction of complexity and the feasibility for real-time processing.

Conclusion

An efficient course resolution multiple-receiver approach for reception of slow fading signals in digital wireless communication systems has been proposed. The case of noncoherent FSK, in case of slow Rayleigh fading and additive Gaussian noise affecting the observations at each individual receiver, has been considered. At each individual receiver, course data is made. All receiver data is sent to a central receiver where final global data is developed which indicates which symbol was transmitted. Performance evaluation of the proposed approach has been provided and compared to that of the optimum low and high resolution approaches. It has been shown that the proposed approach reduces cost and complexity of receiver designs considerably. It has been shown that the use of course resolution approach can improve the performance of the central receiver combiner. It has been shown that the performance of the proposed approach is better than the performance of the optimum low resolution approach and is reasonably close to the performance of the high resolution approach using only few numbers of bits. Thus it is impractical to use more than three or four bits per receiver decision to avoid additional hardware construction without significant performance improvement.

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Author's Contributions

Ashraf M. Aziz: Developed the research idea and organized the study. Coordinated the overall framework and participated in all simulations, discussion, data-analysis as well as contributed to the writing of the manuscript.

Mohamed A. Abdel-Rahman: Organized the study. Coordinated the overall framework and participated in all simulations, discussion, data-analysis as well as contributed to the writing of the manuscript.

Saeed A. Al-Ghamdi: Organized the study. Coordinated the overall framework and participated in all simulations, discussion, data-analysis as well as contributed to the writing of the manuscript.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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