Theoretical Analysis and Modeling of Link Adaptation Schemes in Body Area Networks

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Abstract. Considering the medical nature of the information carried in Body Area Networks (BAN), interference from coexisting wireless networks or even other nearby BANs could create serious problems on their operational reliability. As practical implementation of power control mechanisms could be very challenging, link adaptation schemes can be an efficient alternative to preserve link quality while allowing more number of nodes to operate simultaneously. This paper provides theoretical analysis and Markov chain modeling of interference mitigation schemes such as adaptive modulation and adaptive data rate for body area networks. These schemes are relatively simple and well-suited for low power nodes in body area networks that might be operating in environments with high level of interference.

Keywords: Link adaptation, Interference mitigation, Body area networks, Markov chain, Interference mitigation factor.

1 Introduction

Body Area Networks (BANs) consist of multiple wearable (or implantable) radio-enabled sensors that can establish two-way wireless communication with a controller node that could be either worn or located in the vicinity of the body [1]. These potentially mobile networks are expected to coexist with other wireless devices that are operating in their proximity. Considering the medical nature of the data carried in a BAN, interference from coexisting wireless networks or even other nearby BANs could create a serious problem on the reliability of the network operation. The interference among nodes of a single BAN can be avoided by using multiple access techniques, e.g., TDMA. However, as no coordination exists across multiple BANs, interference may occur when several individuals wearing BAN are within close proximity of each other. This inter-BAN interference could result in performance degradation of the communication link within one network.

To maintain the link quality (e.g. desired received signal strength level or signal to interference and noise ratio (SINR)) in such varying communication channels, efficient power control mechanisms have been proposed [2, 3]. However, practical implementation of such mechanisms for BAN applications could be very challenging,

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particularly in fast changing scenarios when the SINR is varying due to the unpredictable movement of multiple nearby BANs.

Advanced signal processing using interference cancellation techniques [4] has also been proposed to minimize the impact of interference. However, there are two main problems with such techniques especially when it comes to their application in BAN. First is the high complexity of the receiver which makes the implementation of interference cancelation impractical unless the number of nodes is very small. Complexity is especially a critical issue in body area networks. As nodes mainly rely on battery power, prolonging their lifetime is of prime importance. The second problem is that some interference cancellation schemes require knowledge of the channel condition (such as attenuation, phase, and delay) between each of the interferers and the receiver. Obtaining accurate estimates of the channel condition is extremely difficult for body area networks. To overcome the two main problems, a low complexity algorithm was proposed in our previous work [10, 11].

Interference mitigation schemes [5, 6] can be an attractive alternative to interference cancellation particularly in an environment with a high interference level. The principle of the interference mitigation is basically to reduce transmit power by using link adaption schemes. Lowering the transmit power decreases the interference on other networks and therefore allows the possibility of having more networks operating simultaneously. The trade-off in achieving this gain is degradation in other performance measures such as throughput or data rate. In this paper, we focus on theoretical analysis and modeling of our proposed schemes [6] using Markov chain.

The remainder of this paper is organized as follows. The overall system is described in Section 2. Algorithms for the proposed multi-BAN interference mitigation are provided in Section 3. Theoretical analysis and modeling of interference mitigation for multiple BANs are presented in section 4. Finally, simulation results and conclusions are discussed in Sections 5 and 6 respectively.

2 System Description

In a BAN, several nodes form a network with a star topology. These nodes could share the same spectrum in a time-division multiple access manner based on the IEEE 802.15.6 standard. Therefore, there is no interference among the nodes within a single BAN. However, interference may come from other sources, such as nearby BANs or other coexisting non-BAN wireless networks. In the analysis, we focus on the performance at the controller (or master) node of the desired BAN. The Signal to Interference plus Noise Ratio (SINR) [7] at the controller node of BAN i is defined as:

$$SINR_i = \frac{S_i}{N + \sum_{j \neq i} S_j}, \tag{1}$$

where S_i is the received power from the desired transmitter at the controller node of BAN i, S_j is received power from interferer j, and N is additive noise power.

The interference signal may come from any coexisting wireless network including other BANs that are not coordinated with the BAN *i*. Analyzing a special scenario with pre-specified node locations will not provide sufficient information in order to judge effectiveness of the mitigation schemes. Here, we assume that the desired received signal and total interference plus noise power information are available at the controller node of the considered BAN. Based on the available SINR, the controller node may command other nodes to select appropriate interference mitigation scheme.

3 Interference Mitigation for Multiple BANs

The purpose of interference mitigation is to lower the average transmit power using link adaptation schemes while maintaining link quality. Although, this might lead to lower throughput or data rate, it will allow for more number of active networks that can reliably coexist in possible interference rich environment. In low interference scenarios (i.e. normal operational status), all nodes can operate in their default (i.e. normal) mode. For higher levels of interference, one of the interference mitigation schemes will be activated. Here, we propose Interference Mitigation Factor (IMF) as a measure of the effectiveness of such schemes. The IMF is defined as the reduction of transmit power level using a mitigation scheme compared with the normal operational mode. In the next section, we will briefly review our proposed algorithms outlined in [6].

3.1 Adaptive Modulation

We consider a set of MPSK schemes (such as Ω={BPSK, QPSK, 8PSK}) for adaptive modulation due to their similar detection mechanism at the receiver. These modulation schemes can be easily implemented with minor modifications for link adaption. Given a pre-specified BER, the required SINR may be determined based on channel conditions. For higher SINR (i.e. normal operation), the 8PSK scheme is chosen in order to achieve higher bit rate. With an adaptive modulation scheme, QPSK or BPSK may be used to maintain the same BER. This will lower the required transmit power level, which will result in less interference to all other nodes in the neighboring BANs.

Two thresholds $\{\gamma_H, \gamma_L\}$ are considered to determine the range of adaptation within the set of modulation schemes. When SINR is higher than the higher threshold (i.e. γ_H), 8PSK scheme is used. Likewise, BPSK is chosen when SINR is lower than the lower threshold (i.e. γ_L). QPSK is used when the SINR is between the two thresholds. Since SINR may be changing rapidly in practice, a weighting factor α_M is introduced to maintain a running average of SINR over a fast changing channel. The algorithm for adaptive modulation scheme was presented in [6]. For adaptive modulation, the interference mitigation factor, when 8PSK is used as the normal mode, is defined as:

$$IMF(dB) = P_{8PSK}(dBm) - P_S(dBm) = 10\log\left(P_{8PSK}(watt)/P_S(watt)\right), \tag{2}$$

where P_{8PSK} and P_S are the required transmit power for 8PSK and the chosen modulation scheme, *S*, respectively. The IMF is a function of SINR and channel condition.

3.2 Adaptive Data Rate

The second mitigation scheme is adaptive data rate. The data rate is divided into *M* steps between the maximum and minimum values $R_{\max}$ and $R_{\min}$. The data rate is operated at $R_{\max}$ in the normal mode and is changed by comparing the weighted sum of SINR with the target SINR. The weighted sum (with an appropriate weighting factor $0 < \alpha_R < 1$) is used to smooth significant variation and fluctuation of SINR. A hysteresis factor Δ_R is also used to minimize possible ping-pong effect between the two data rates. The algorithm for interference mitigation using adaptive data rate was proposed in [6]. The relationship between the transmit power (*S*) and data rate (*R*) is:

$$\frac{E_b}{I_o + N_o} = \frac{S}{I_o + N_o}\frac{1}{R} \tag{3}$$

where E_b, I_o, and N_o are bit energy, interference and noise spectral density, respectively. To keep the same required $E_b/(I_o + N_o)$, the transmit power and the data rate must be proportional. The higher the data rate, the more transmit power is required. Therefore, the instantaneous interference mitigation factor, when R_1 is the data rate in the normal mode, is defined as:

$$IMF = 10 \cdot \log\frac{S_1}{S_f} = 10 \cdot \log\frac{R_1}{R_f}\ (\mathrm{dB}), \tag{4}$$

where S_1 and S_f are the corresponding transmit powers for the rates R_1 and R_f, respectively.

4 Theoretical Analysis

4.1 Autoregressive Process of Order 1 for SINR

As shown in Algorithms 1-2 [6], a weighted sum of SINR is used for the proposed adaptive schemes. This weighted sum of SINR may be rewritten in general form as below.

$$\bar{\gamma}_i = \alpha \cdot \gamma_i + (1-\alpha) \cdot \bar{\gamma}_{i-1}, \tag{5}$$

where γ_i is assumed to have independent and identical distributions (*i.i.d.*) at discrete time $i \in \{-\infty,\ldots-1,0,1,2,\ldots\infty\}$ and α is a weighting scalar. Thus $\bar{\gamma}_i$ is a recursive form of an autoregressive process of order 1 (i.e. AR(1)) [8]. If $|1-\alpha|<1$, the process of $\bar{\gamma}_i$ is stationary. Practically, the weighting scalar is chosen between 0.5 and 1. (Note that the discrete random process $\bar{\gamma}_i$ remains identically distributed for all *i*, but not independent except when $\alpha=1$.) If γ_i has a common mean μ and variance σ^2, the mean and variance of $\bar{\gamma}_i$ (unconditional case) are constant and independent of *i* and may be obtained as below.

$$\mu_{un} = E(\bar{\gamma}_i) = \mu \quad \text{and} \quad \sigma_{un}^2 = Var(\bar{\gamma}_i) = \alpha\sigma^2/(2-\alpha) \tag{6}$$

On the other hand, the mean and variance of $\bar{\gamma}_i$ given $\bar{\gamma}_{i-1}$ (conditional case) can be expressed by:

$$\mu_c = E(\bar{\gamma}_i \mid \bar{\gamma}_{i-1} = z) = \alpha\mu + (1-\alpha)\text{z}, \text{ and } \sigma_c^2 = Var(\bar{\gamma}_i \mid \bar{\gamma}_{i-1} = z) = \alpha^2\sigma^2 \tag{7}$$

Note that the SINR measurements γ_i is not necessarily a Gaussian process. However, if γ_i is a Gaussian process, then $\bar{\gamma}_i$ will also be a Gaussian process for both unconditional and conditional cases. In other non-Gaussian cases, the central limit theorem indicates that $\bar{\gamma}_i$ will be approximately Gaussian when α is close to zero. The theoretical analysis under the Gaussian assumption has been provided in the following two subsections (4.2 and 4.3). For the non-Gaussian case with given distribution $\bar{\gamma}_i$, the formula can also be derived in a similar way.

4.2 Model for Adaptive Modulation

From the discussion in the previous section, we realize that $\bar{\gamma}_i$ has an identical distribution for each *i*. In this approach, a modulation scheme is chosen at any time instant *i* according to the predefined thresholds and the distribution of $\bar{\gamma}_i$ as shown in Algorithm 1 [6]. Therefore, the steady state probabilities of having BPSK, QPSK or 8PSK may be easily obtained as below.

$$\begin{aligned}
\pi(BPSK) &= P_r\{\bar{\gamma}_i < \gamma_L\} \\
\pi(8PSK) &= P_r\{\bar{\gamma}_i > \gamma_H\} \\
\pi(QPSK) &= P_r\{\gamma_L \le \bar{\gamma}_i \le \gamma_H\}
\end{aligned} \tag{8}$$

If $\bar{\gamma}_i$ has a Gaussian distribution with mean and standard deviation as shown in Eq. (6), then the steady state probabilities are given by:

$$\pi(BPSK) = P_r\{\bar{\gamma}_i < \gamma_L\} = 1 - Q\{(\gamma_L - \mu_{un}) / \sigma_{un}\} \tag{9}$$

$$\pi(8PSK) = P_r\{\bar{\gamma}_i > \gamma_H\} = Q\{(\gamma_H - \mu_{un}) / \sigma_{un}\} \tag{10}$$

where

$$Q(x) = \int_x^{\infty} \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du \ . \tag{11}$$

From Equations (2) and (8), the average IMF for the adaptive modulation is obtained as.

$$IMF_{avg}(dB) = 10\log\left(\frac{P_{8PSK}(watt)}{\sum_{s\in\Omega} \pi(s) P_s(watt)} \right) \tag{12}$$

4.3 Model for Adaptive Data Rate

From Algorithm 2 [6], and when $\alpha = 1$, the adaptive data rate forms a finite state Markov process. For $\alpha \neq 1$, this will not be the case since the distribution of $\bar{\gamma}_i$ will depend on the prior events. However, given the conditional distribution of $\bar{\gamma}_i$, the process of adaptive data rate will still be a Markov process, and more specifically, a birth-death process. If $\bar{\gamma}_i$ has a Gaussian distribution, its mean and variance may be obtained from Eq. (7). And, its conditional distribution will be *i.i.d.* As a result, the birth and the death rates will be independent of the state as shown in Fig. 1. In other words, the transition probabilities of the birth-death process (p and q) are constant and can be calculated by:

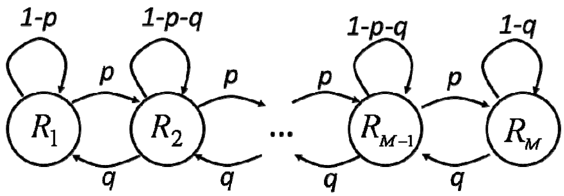

Fig. 1. Markov Process Model for Adaptive Data Rate

$$p = p_{m,m+1} = P_r\{\bar{\gamma}_i < \hat{\gamma} - \Delta_R\} = 1 - Q\left\{(\hat{\gamma} - \Delta_R - \mu_c) \Big/ \sqrt{\frac{\alpha}{2-\alpha}} \cdot \sigma_c \right\} \tag{13}$$

$$q = p_{m,m-1} = P_r\{\bar{\gamma}_i > \hat{\gamma} + \Delta_R\} = Q\left\{(\hat{\gamma} + \Delta_R - \mu_c) \Big/ \sqrt{\frac{\alpha}{2-\alpha}} \cdot \sigma_c \right\} \tag{14}$$

Given p and q in Equations (13) and (14), the conditional steady state probability of R_m, given $\bar{\gamma}_{i-1} = z$, is $\pi_z(R_m)$ and may be obtained by solving the following set of equations.

$$\begin{cases} \pi_z(R_j) = \sum_{m=1}^{M} p_{m,j} \cdot \pi_z(R_m) \\ \sum_{m=1}^{M} \pi_z(R_m) = 1 \end{cases} \tag{15}$$

The first equation of this set may be rewritten in matrix form as below.

$$\begin{bmatrix} \pi_z(R_1) \\ \pi_z(R_2) \\ \vdots \\ \pi_z(R_{M-1}) \\ \pi_z(R_M) \end{bmatrix} = \begin{bmatrix} 1-p & q & \cdots & 0 & 0 \\ p & 1-p-q & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1-p-q & q \\ 0 & 0 & \cdots & p & 1-q \end{bmatrix} \begin{bmatrix} \pi_z(R_1) \\ \pi_z(R_2) \\ \vdots \\ \pi_z(R_{M-1}) \\ \pi_z(R_M) \end{bmatrix} \tag{16}$$

From (15), the conditional steady state probabilities $\pi_z(R_m)$, $m=1,2,\ldots, M$, of the Markov process are given by

$$\pi_z(R_m) = \frac{(p/q)^{m-1}}{\sum_{i=1}^{M} (p/q)^{i-1}} = \begin{cases} \dfrac{(p/q)^{m-1} - (p/q)^m}{1-(p/q)^M} & \text{if } p \neq q \\ 1/M & \text{if } p = q \end{cases} \tag{17}$$

With a Gaussian assumption and Eq. (6), the distribution of $\bar{\gamma}_{i-1}$ is given by

$$P_r(\bar{\gamma}_{i-1} = z) = \frac{1}{\sqrt{2\pi}\sigma_{un}} \exp\left(\frac{-(z-\mu_{un})^2}{2\sigma_{un}^2} \right). \tag{18}$$

Thus, the unconditional steady state probabilities $\pi(R_m)$, $m=1,2,\ldots, M$, of the Markov process are given by

$$\pi(R_m) = \int_{-\infty}^{\infty} \pi_z(R_m) \frac{1}{\sqrt{2\pi}\sigma_{un}} e^{-(z-\mu_{un})^2 / 2\sigma_{un}^2} du . \tag{19}$$

The average IMF for adaptive data rate may be obtained by combining Equations (4) and (19) as below.

$$IMF_{avg} = 10 \cdot \log \frac{R_1}{\sum_m R_m \cdot \pi(R_m)} \text{ (dB)} \tag{20}$$

From Equations (13), (14) and (17), the following special scenarios can be observed.

(i) if $\hat{\gamma} = \mu_c$, then $p=q$ and the steady state probabilities are equal to $1/M$ for all data rates of R_m. Also the average IMF is a constant and independent of σ.

(ii) if $\hat{\gamma} = \mu_c$, the value of p (and q) decreases while Δ_R increases.

(iii) if $\Delta_R = 0$, then $p + q = 1$.

(iv) if $p > q$, the steady state probability of R_m increases with m. That is, the data rate becomes lower in order to decrease interference level.

5 Simulation Results

The channel model used is that of body surface to external nodes at 2.4 GHz as outlined in [7]. The effect of shadowing has been considered by a lognormal distribution with standard deviation of 3.80 dB for a hospital room [7]. Assume that there exists co-channel interference from other BANs as well as other non-BAN networks. Also, assume that each one of the BAN interferers is causing the same level of interference. Due to higher transmit power; the non-BAN interferer usually causes higher levels of interference. We also assume that the distribution of shadowing for all interferers is identical (i.e. lognormal distribution with the same standard deviation). Therefore, the SINR values can be generated based on the lognormal distributions. Note that the distribution of total interference plus noise is not log-normal. However, an approximation of lognormal distribution may be used if one of the interference signals is dominant. In our simulation, we have not used this approximation. In the theoretical analysis, however, the lognormal distribution assumption was made for interference plus noise. The comparison between simulation and theoretical results will therefore highlight the validity of this assumption. The average IMF will be evaluated in terms of signal to other BAN interference ratio plus noise, S / I_{BAN} and non-BAN to BAN interference ratio, $I_{non-BAN} / I_{BAN}$.

5.1 Adaptive Modulation

The adaptive modulation schemes considered in our simulation include BPSK, QPSK, and 8PSK. To select the thresholds γ_H and γ_L, BER performance of modulation schemes over AWGN channel is used. At BER=0.1%, the required SNR values are 6.8 dB, 9.8 dB and 14.8 dB for BPSK, QPSK and 8PSK, respectively [9]. Therefore, we choose $\gamma_H = 12dB$, $\gamma_L = 8dB$. These threshold values may be adjusted with channel conditions if necessary. The interferers include 3 other close-by BANs and one non-BAN interferer. Let S be the desired received signal power. Define I_{BAN} to be the received interference power from each BAN interferer; likewise, define $I_{non-BAN}$ to be the received interference power from a non-BAN source. The results shown in Fig. 2 indicate a good agreement between simulation and theoretical analysis. As expected, given the same S / I_{BAN} , higher non-BAN interference levels will lead to higher average IMF. And under those circumstances, BPSK is the choice for the modulation scheme since it requires lower transmit power for a given BER. Higher average IMF is also observed at lower values of S / I_{BAN} .

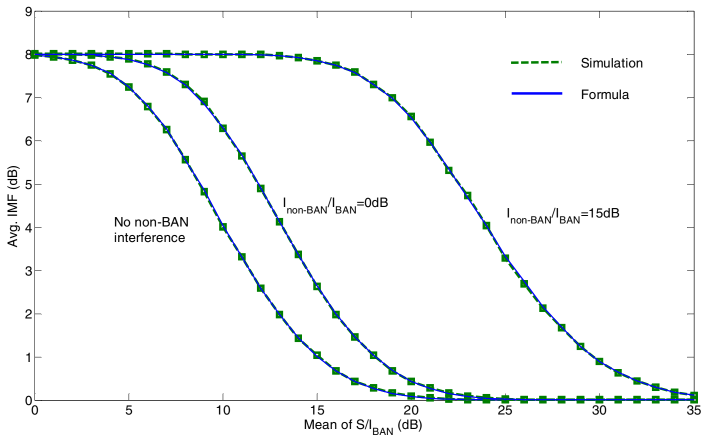

Fig. 2. Interference mitigation using adaptive modulation at $\alpha_M = 0.8$

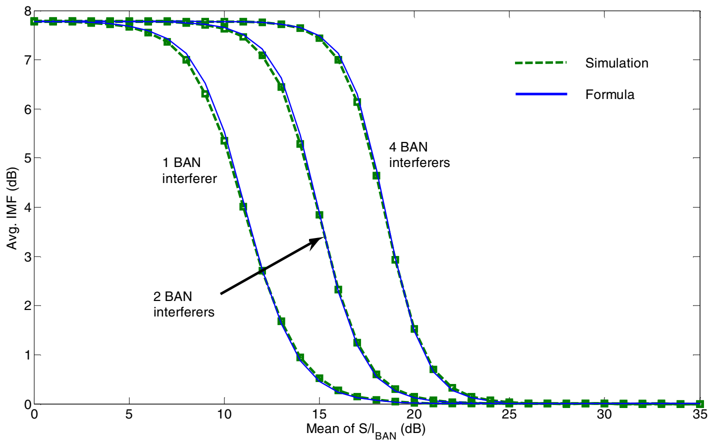

Fig. 3. Interference mitigation using adaptive data rate

5.2 Adaptive Data Rate

Average interference mitigation factors in terms of mean of SINR and number of BAN interferers using adaptive data rate scheme are shown in Fig. 3. The mean of S/I_{BAN} at the x-axis is the ratio of signal to one BAN interference. All the BAN interfering signals have statistics with the same mean and standard deviation. The total interference power is calculated by summing total interference power, where the number of BAN interferers is from 1, 2 and 4. The data rates may be chosen in accordance with the quality of service (QoS) requirements. The set of data rates in the simulation is assumed to be {600, 400, 200, 100} kbps while $\alpha_R = 0.8$, $\Delta_R = 2.0\,\text{dB}$

and $\hat{\gamma} = 12dB$. As expected, the more BAN interferers, the more the average IMF, which requires a lower data rate. For lower mean of SINR cases, higher average IMF values are observed. This effectively means a lower data communication rate for the link at the lower mean of SINR cases. Again, the results shown in Fig. 3 using simulation and theoretical formula match very well.

6 Conclusion

In this paper, we have proposed and analyzed two interference mitigation schemes including adaptive modulation and adaptive data rate. A quantitative measure called the interference mitigation factor was used to evaluate the effectiveness of these schemes in body area networks applications. These schemes are relatively simple and well-suited for very low power nodes in body area networks that might be operating in environments with high interference level. Theoretical analysis to assess the performance of these schemes has also been provided. Results of the theoretical analysis show a close match with simulations. This theoretical analysis is particularly helpful to determine or optimize the parameters used in the adaptive schemes.

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