Mitigation of Channel Diversity and Indoor Channel Modeling for Remote Patient Monitoring Systems

Amit Sehgal, Rajeev Agrawal
G. L. Bajaj Institute of Technology and Management
amitsehgal09@rediffmail.com, rajkecd@gmail.com

Sweta Sneha
Computer Science & Information Systems Department, Kennesaw State University, Kennesaw, GA 30144
ssneha@kennesaw.edu

ABSTRACT
The continuously increasing demand for better healthcare services has added another application to the sphere of remote monitoring services. This extension to e-Health and Telecare services is known as Remote Patient Monitoring (RPM). The direct impact of this application on human life has made it a mission critical application. The randomness and diversity in location and movement profile of patients and Doctors further complicates the modeling and analysis of this system. This paper concentrates on the mitigation of the diversity in communication links involved in the entire system and a decision rule based adaptive indoor channel model. This paper highlights the diversity modeling of wireless channels due to variations in location phenomenon along with movement of the user through a four state Markov Model. From this model, one state corresponding to indoor channel (representing pre or post hospital monitoring) has been analyzed. It suggests the use of an adaptive model with corresponds to a decision rule as per the local conditions of the user and the best suited value representing a model is selected to capture the randomness of the received signal. It is established that the proposed techniques predicts more real values of QoS parameters such as Bit Error Rate (BER) and Outage probability, leading to a higher reliability of wireless channels. It is also shown that the proposed model can be a best fit for this mission critical application - remote patient monitoring - through wireless communication

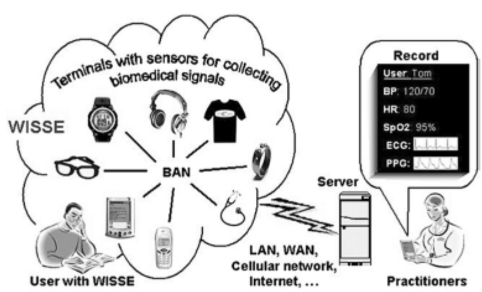
Keywords: wireless channel diversity, adaptive fading model, decision rule, patient monitoring, bit-error-rate, outage probability

1. INTRODUCTION

With the advances in sensor and communication technology, the sphere of application areas for remote monitoring has several inclusions to it e.g. vehicle monitoring, terrain monitoring, machine monitoring etc. A current development in wireless communications integrated with new research in pervasive and wearable biomedical sensor technologies has a radical impact on future health-care services. Some of the major challenges in implementing these services are access to the service for large segment of population, continuous healthcare cost inflation, and demand for sustained quality beyond geographic distribution. From this domain, another remote monitoring system called Remote Patient Monitoring (RPM) is under development for social and commercial acceptance by various entities involved. Fig. 1 shows one such proposed system.

The body sensor networks deployed for patient monitoring assist the healthcare professionals in managing and providing their expertise during chronic or critical illness [1]. It being a mission critical application, a certain set of QoS requirements on network performance must be satisfied which demands high level of reliability, guaranteed bandwidth, short end-to-end delay and minimum bit or packet error rate. Current health care system focuses on the work towards developing a structured and optimized system for reacting to crisis and managing illness. In [2], a prototype of 3G wireless network based mobile teletrauma system was developed. The system uses a desktop installed in an ambulance and the patient information e.g. video/medical images like ultrasound, electrocardiogram (ECG) signals, blood pressure etc. can be transmitted simultaneously through a cellular network. This system was developed with the objective to assist healthcare centres, providing pre-hospital care for the patients present at remote locations. Scheduling of data transmission with different QoS requirements is done using a software-radio based approach. A similar system to provide communication between an ambulance and the hospital was presented in [3]. This system was however, based on Universal Mobile Telecommunication System (UMTS).

In [1], the complexities associated with the process of ubiquitous patient monitoring through emerging technologies were explored. The key contribution of this work is a framework, that captures the complex processes, the parameters involved, and the decision criteria for ubiquitous patient monitoring. A conceptual model of ubiquitous patient monitoring was developed by leveraging the proposed framework, the same was validated by a usage scenario. The opportunities and challenges of ubiquitous patient monitoring were also detailed in this publication [1].



Wearable intelligent sensors and systems for e-medicine (WISSE)

Figure 1: Wireless network based remote patient monitoring system
(Source: Guest Editorial Introduction to the Special Section on M-Health: Beyond Seamless Mobility and Global Wireless Health-Care Connectivity by Robert S. H. Istepanian, Emil Jovanov, Y. T. Zang)

In [4], a Global System for Mobile Communication (GSM) for out-of-hospital follow-up service was proposed, specifically for cardiac patients. This service was designed to facilitate monitoring of data transmission between the patients and the healthcare professionals. The measurement devices were connected to the GSM network through mobile equipments. The wireless data transmission was done using Wireless Application Protocol (WAP).

In [5], the implementation and validation of a prototype of a Remote Patient Monitoring (RPM) system based on wireless technology using a pervasive device (such as a cellular phone) was described to send an SMS (Short Message Service) to the medical staff. The proposed system provides an easy, viable, cheap and effective way for transmitting vital information to the healthcare providers. It also monitors patient's health status, such as SpO_2 (oxygen percentage in blood), heart rate, and temperature. This system combines Global System for Mobile (GSM) and Global Positioning System (GPS) for health monitoring.

Another architecture of remote patient monitoring was presented in [6], with a provision of help at home with wearable devices and wireless transmission methods. The work was based on the increasing need for efficient management of emergency messages, originating from portable and wearable devices as well as demand for such an efficient management scheme for mobile units which provide help at home. Major contribution of this work was to provide help at home in an efficient manner, minimizing the service time while maintaining high availability for the high priority calls. An algorithm to enable the management of such prioritized messages, managing the mobile units providing assistance at home in an efficient manner was also proposed in this work.

Sunil Kumar, Kashyap Kambhatla et al. in [7] provided an overview of an architecture and QoS characteristics of the telecardiology systems via mobile technologies. The challenges faced were highlighted in this work while implementing such an integrated system viz.

1. The hardware must be wearable and reliable as it will be worn for long periods of time in various environments.
2. As the interference from multiple sensors will be random. Therefore, Sensor communication to a base-station needs to be analyzed/modeled.
3. The communication from base-station to doctor must traverse through multiple networks (3G, WiFi, 4G, Bluetooth, etc.) with different packet size requirements and data loss parameters.

In [8], various challenges issues and implementation strategy of Wireless Sensor Networks for Personal Health Monitoring were discussed. Further, the use of Wearable Wireless Body Area Networks as a key infrastructure enabling unobtrusive, continual, ambulatory health monitoring was demonstrated. A general Wearable Wireless Body/Personal Area Network (WWBAN) architecture was also described along with important implementation issues, and a prototype WWBAN based on off-the-shelf wireless sensor platforms and custom-designed ECG and motion sensors was also introduced. Several key technical issues such as sensor node hardware architecture, software architecture, network time synchronization, and energy conservation were addressed. Aspects like improvement of QoS of wireless communication, reliability of sensor nodes, security, and standardization of interfaces and interoperability were left untouched in the work.

Due to the wide diversity of the environment and terrain profiles and severe constraints on supporting technologies in remote/rural areas, it becomes a challenge to evaluate the network performance. Under such conditions, any better model which can provide an effective alternative approach to the design and analysis of the networks will enhance the use of wireless technologies in the field of patient monitoring. Further, the radio link is highly dynamic due to random nature of the received signal, as a result of the effect of shadowing and fading which needs probabilistic framework. This makes modeling of wireless channel, a more complex task. In context to remote patient monitoring, the diversity of these channels is further increased due to the movement and diverse location of the patient. In the proposed work, a decision rule has been defined to obtain an adaptive indoor channel model which models all possible wireless link characteristics ranging from Line-of-Sight (LOS) to Non-Line-of-Sight (NLOS) conditions.

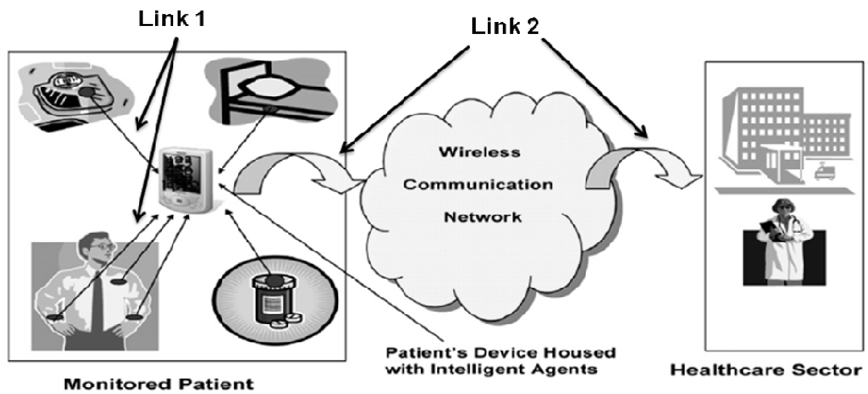


Figure 2: Framework of patient monitoring system.

In previous works, the framework for wireless patient monitoring system proposed by Sweta Sneha and Upkar Varshney [1] involves two different types of wireless links. Fig. 2 shows these links viz. (i) Link 1: between body sensors and patient device (coordinator) e.g. PDA and (ii) Link 2: between coordinator device and healthcare professional. The Link 1 is a case of short term channel modeling since the patient device is assumed to be present close to the patient, wearing the sensors. The Link 2 is a case of long term channel modeling and includes a wide diversity due to variable local features and distance. In addition to this, the complexity of both the links is further added by the presence of human body in close proximity of the coordinator device, almost always, which leads to body shadowing effect [9]. Since the overall link between the body sensors and healthcare professional is closely dependant on the location of the patient which is highly diverse and dynamic, an decision rule based adaptive channel modeling is required to capture the phenomenon of signal variation for such systems.

2. MODELING MOVEMENT/LOCATION OF THE PATIENT

To capture the movement of a patient, we have used a three state Markov model shown in fig. 3 representing the movement profile of the patient. These states and their corresponding channel models representing the location of the patient (State A, State B and State C) viz. (i) State A - patient present in a room and movement is restricted to within the room, (In-channel model), (ii) State B - patient present in a partially open area like balcony of the house or building, (Partial In-channel model) and (iii) State C - patient present in wide open area, (Out-channel model). The possible state transitions considered in our model is:

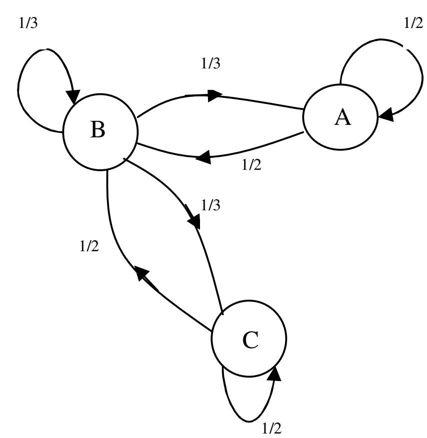


Figure 3: Markov's Model representing movement of the patient

The transition probability matrix of single transition from one state to another state as per fig. 2.0 can be obtained as:

$$P_{Transition} = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/3 & 1/3 & 1/3 \\ 0 & 1/2 & 1/2 \end{bmatrix} \quad (1)$$

In state B, the patient is assumed to be present just outside the room and is in a partially open area. This state can further be decomposed into two sub states viz State B1 and State B2. State B1 represents the situation where the patient moves out of the room without carrying the coordinator device. Whereas, State B2 represents the condition when the patient has moved out of the room and is carrying his/her device. The Markov's model can now be represented as shown in fig. 4:

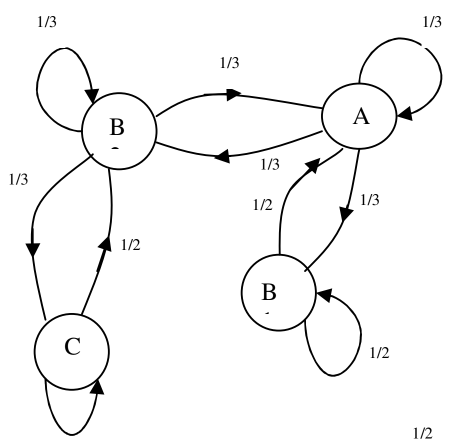


Figure 4: Modified Markov's model

The transition probability matrix for all possible single step state transition is given as:

$$P^1_{Trans} = \begin{bmatrix} 1/3 & 1/3 & 1/3 & 0 \\ 1/3 & 1/3 & 0 & 1/3 \\ 1/2 & 0 & 1/2 & 0 \\ 0 & 1/2 & 0 & 1/2 \end{bmatrix} \quad (2)$$

In transition matrix P^1_{Trans}, the probability of transition between some states is zero as in case of transition from state A to state C there is no direct path however, it is possible only through intermediate state B2. A two step transition matrix can be calculated using Chapman – Klomogrov (C-K) Equation [10] given as: $P^{(n+m)} = P^{(n)}.P^{(m)}$ where $P^{(n)}$ denotes the matrix of n-step transition probabilities P^n_{ij}. Using this equation the two step transition matrix can obtained as:.

$$P^2_{Trans} = P^{1+1}_{Trans} = P^1_{Trans} \cdot P^1_{Trans}$$

P^2_{Trans} represents the two step transition probability from state A to state C via state B2 which is 5/18 and for the reverse transition from state C to state A via state B2 is 1/6.

$$P^2_{Trans} = \begin{bmatrix} 1/3 & 1/3 & 1/3 & 0 \\ 1/3 & 1/3 & 0 & 1/3 \\ 1/2 & 0 & 1/2 & 0 \\ 0 & 1/2 & 0 & 1/2 \end{bmatrix} \cdot \begin{bmatrix} 1/3 & 1/3 & 1/3 & 0 \\ 1/3 & 1/3 & 0 & 1/3 \\ 1/2 & 0 & 1/2 & 0 \\ 0 & 1/2 & 0 & 1/2 \end{bmatrix} \quad (3)$$

$$= \begin{bmatrix} 7/18 & 2/9 & 5/18 & 1/9 \\ 2/9 & 7/18 & 1/9 & 5/18 \\ 5/12 & 1/6 & 5/12 & 0 \\ 1/6 & 5/12 & 0 & 5/12 \end{bmatrix}$$

Similarly, the two step transition probability from state B1 to B2 is 1/6 and the reverse is 1/9. The probability of transition from state B1 to state C is still zero since it is assumed here that the patient will always carry the co-ordinator device with him/her, while going to regions represented by state C. So, as shown in figure 2.0, he/she must go back to state A from B1 and then through B2 the patient can go to state C. Similarly, the probability of transition from state C to state B1 in one or two transitions is zero. Therefore, we now calculate three step transition probability matrix using C-K equation.

$$P^3_{Trans} = P^{2+1}_{Trans} = P^2_{Trans} \cdot P^1_{Trans}$$

$$= \begin{bmatrix} 7/18 & 2/9 & 5/18 & 1/9 \\ 2/9 & 7/18 & 1/9 & 5/18 \\ 5/12 & 1/6 & 5/12 & 0 \\ 1/6 & 5/12 & 0 & 5/12 \end{bmatrix} \cdot \begin{bmatrix} 1/3 & 1/3 & 1/3 & 0 \\ 1/3 & 1/3 & 0 & 1/3 \\ 1/2 & 0 & 1/2 & 0 \\ 0 & 1/2 & 0 & 1/2 \end{bmatrix}$$

$$= \begin{bmatrix} 0.342 & 0.259 & 0.268 & 0.129 \\ 0.259 & 0.342 & 0.129 & 0.268 \\ 0.403 & 0.194 & 0.347 & 0.055 \\ 0.194 & 0.403 & 0.055 & 0.347 \end{bmatrix} \quad (4)$$

Finally from the matrix P^3_{Trans}, we get a non-zero probability of transition from state B1 to C and reverse transition in three steps which was zero in initial two steps.

3. CHANNEL MODELING

In this section, we will analyze the link between body sensor nodes and coordinator device representing the scenario when both the patient and the coordinator device are present inside a room.

It is interesting to note that the presence of the patient and the coordinator device in the same room does not guarantee the availability of LOS signal, the channel characteristics will change with movement of the patient within the room. Assuming that all the sensors are deployed on the front of the body and the coordinator device is also present in front of the patient, a strong LOS component will be available with various multipath components. In such scenario assuming that the signal variation follows Nakagami-n distribution having pdf $p_{N-n}(x)$ given as [11]:

$$p_{N-n}(x) = \frac{2(1+n^2)e^{-n^2}x}{y}\exp(-\frac{(1+n^2)x^2}{y}) I_o(2nx\sqrt{\frac{1+n^2}{y}}) \quad (5)$$

where n is the Nakagami-n fading parameter, which ranges from 0 to ∞. This parameter is related to the Rician K factor by K = n^2 which corresponds to the ratio of power of LOS component to the average power of multipath components. Replacing $(1+n^2)/y$ by d, Eq. (5) can, now, be re-written as:

$$p_{N-n}(x) = 2de^{-n^2}x\exp(-dx^2)I_o(2nx\sqrt{d}) \quad (6)$$

The modified Bessel function $I_v(z)$ can is represented as [13]:

$$I_v(z) = \sum_{k=o}^{\infty}\frac{(z/2)^{2k}}{(k!)^2} \quad (7)$$

For v = 0 and z = $(2nx(d)^{1/2})$, eq. (7) can be rewritten as:

$$I_0(2nx\sqrt{d}) = \sum_{k=o}^{\infty}\frac{(nx\sqrt{d})^{2k}}{(k!)^2} \quad (8)$$

Substituting eq. (8) in eq. (6), we get:

$$p_{N-n}(x) = 2de^{-n^2}x\exp(-dx^2)\sum_{k=o}^{\infty}\frac{(nx\sqrt{d})^{2k}}{(k!)^2} \quad (9)$$

When the patient changes direction or position within the room, the coordinator device may now be present on the side or back of the patient. The signal component changes gradually from LOS to NLOS. In the later case, there is no or small LOS component however, various multipath components reach the coordinator device through reflection, diffraction and/or scattering. The signal variation, in the extreme NLOS case follows Nakagami-m distribution, with m=1, having pdf $p_{N-mLN}(x)$. The pdf of general Nakagami-m distributed variate X conditioned on random variable Y representing average power is expressed as [14]:

$$p_{N-m}(x\,|\,Y=y) = \frac{2m^m x^{2m-1}}{\Gamma(m)y^m}\exp(-\frac{m}{y}x^2), x>0 \quad (10)$$

where $\Gamma(m)$ is the gamma function. For the NLOS propagation, m=1 so that Nakagami distribution closely follows Rayleigh distribution which is the widely accepted distribution for NLOS indoor propagation.

3.1 Decision Rule

A simple two states (with and without LOS) model can be represented as a convex combination of LOS multipath and NLOS multipath fading which is characterized by a time sharing factor A. The factor 'A' takes binary values (0 and 1) based on the output of a comparator which compares outage probability of LOS multipath fading (P_{out}^{LOS}) with a preset value (P_{out}^{th}). This factor 'A' also represents the condition for transition from LOS channel model to NLOS channel model. The comparator works according to the following rule:

$$A = \begin{cases} 0, \ if \ P_{out}^{LOS} < P_{out}^{th} \rightarrow \text{LOS channel model (eq. 6)} \\ 1, \ if \ \mathrm{P}_{\mathrm{out}}^{\mathrm{LOS}} \geq P_{out}^{th} \rightarrow \text{NLOS channel model (eq. 7)} \end{cases} \quad (11)$$

The resulting combined pdf is given by:

$$p(x) = (1-A)\,p_{N-n}(x) + A\,p_{N-m}(x) \quad (12)$$

where $p_{N-n}(x)$ is given by eq. (9) whereas $p_{N-m}(x)$ is given by eq. (10).

4. QoS PARAMETER ESTIMATION FOR THE PROPOSED MODEL

4.1. Outage Probability:

The outage probability is an important performance criterion for the diversity systems operating over fading channels. It corresponds to the probability that the signal envelope or the SNR falls below a pre-determined threshold value. In terms of SNR, it can be calculated as: $P_{out} = \int_0^{\gamma_{th}} p_\gamma(\gamma)d\gamma$

where $p_\gamma(\gamma)$ is the probability distribution function (pdf) of SNR. We, now, present a closed form solution of the outage probability for LOS channel represented by P_{out}^{LOS}.

Using variable transformation given in [12], eq. (6) will have a form:

$$p_{N-n}(\gamma) = \frac{(1+n^2)e^{-n^2}}{\bar{\gamma}}\exp(-\frac{(1+n^2)\gamma}{\bar{\gamma}}) I_o(2n\sqrt{\frac{(1+n^2)\gamma}{\bar{\gamma}}}) \quad (13)$$

where γ is instantaneous SNR and $\bar{\gamma}$ is average SNR.

For Nakagami-n distribution, the outage probability can be calculated using eq. (13):

$$P_{out}^{LOS} = \int_0^a \frac{(1+n^2)e^{-n^2}}{\bar{\gamma}} \exp(-\frac{(1+n^2)\gamma}{\bar{\gamma}}) I_o(2n\sqrt{\frac{(1+n^2)\gamma}{\bar{\gamma}}}) d\gamma$$
$$= \frac{(1+n^2)e^{-n^2}}{\bar{\gamma}} \int_0^a \exp(-\frac{(1+n^2)\gamma}{\bar{\gamma}}) I_o(2n\sqrt{\frac{(1+n^2)\gamma}{\bar{\gamma}}}) d\gamma \quad (14)$$

Let $\frac{1+n^2}{\bar{\gamma}}$ =b. The modified Bessel function $I_o(2n\sqrt{\frac{(1+n^2)\lambda}{\bar{\gamma}}})$ can be written as $\sum_{k=0}^{\infty} \frac{(n\sqrt{b\gamma})^{2k}}{(k!)^2}$ [14].

Now, P_{out}^{LOS} can be calculated as:

$$P_{out}^{LOS} = be^{-n^2} \sum_{k=0}^{\infty} \left[\frac{(n\sqrt{b})^{2k}}{(k!)^2} \int_0^a \exp(-b\gamma)\gamma^k d\gamma \right]$$
$$= be^{-n^2} \sum_{k=0}^{\infty} \left[\frac{(n\sqrt{b})^{2k}}{(k!)^2} b^{-k-1} \int_0^a t^k e^{-t} dt \right] \quad (15)$$

4.2. BER estimation:

BER is the practical equivalent term for Probability of Error (P_e) and represents channel performance as a function of available (C/N) ratio. BER = f(C/N) and/or BER = f(E_b/N_o) where E_b is average energy of modulated bit and N_o is noise power spectral density. To analyze the performance of the proposed model we have calculated BER performance of linearly amplified and coherently modulated Quadrature Phase Shift Keying (QPSK) system for a stationary AWGN channel which is widely used modulation scheme for wireless communication. The probability of error for QPSK is expressed as $P_e = \frac{1}{2} erfc\sqrt{\frac{E_b}{N_o}}$ [15].

In the above expression, noise density N_o does not change with fading and E_b is constant in a stationary AWGN environment. To obtain the BER in a faded environment, we define a random variable α which follows fading distribution. The modified expression for BER is:

$$P_e(\gamma) = \frac{1}{2} erfc\sqrt{\gamma} \text{ where } \gamma = \alpha^2 \frac{E_b}{N_o} \quad (16)$$

Probability of bit error (P_e) for a faded channel having P(γ) as pdf of fading can be calculated as:

$$P_e = \int_0^{\infty} \frac{1}{2} erfc\sqrt{\gamma} P(\gamma) d\gamma \quad (17)$$

For a channel having fading pdf given by eq. (13), probability of bit error or BER can be written as:

$$P_e = \int_0^{\infty} \frac{1}{2} erfc\sqrt{\gamma} \frac{(1+n^2)e^{-n^2}}{\bar{\gamma}} \exp(-\frac{(1+n^2)\gamma}{\bar{\gamma}}) I_o(2n\sqrt{\frac{(1+n^2)\gamma}{\bar{\gamma}}}) d\gamma \quad (18)$$

Let $\frac{1+n^2}{\bar{\gamma}} = g$. Now, eq. (18) can be written as:

$$P_e = \int_0^{\infty} \frac{1}{2} erfc\sqrt{\gamma}\ ge^{-n^2} \exp(-g\gamma) I_o(2n\sqrt{g\gamma}) d\gamma \quad (19)$$

$$= \frac{1}{2} ge^{-n^2} \int_0^{\infty} erfc\sqrt{\gamma}\ \exp(-g\gamma) I_o(2n\sqrt{g\gamma}) d\gamma \quad (20)$$

$$= \frac{1}{2} ge^{-n^2} \int_0^{\infty} erfc\sqrt{\gamma}\ \exp(-g\gamma) \sum_{k=0}^{\infty} \frac{(n\sqrt{g\gamma})^{2k}}{(k!)^2} d\gamma \quad (21)$$

$$= \frac{1}{2} ge^{-n^2} \sum_{k=0}^{\infty} \frac{(n\sqrt{g})^{2k}}{(k!)^2} \int_0^{\infty} erfc\sqrt{\gamma}\ \exp(-g\gamma)\gamma^k d\gamma \quad (22)$$

$$= 0.5e^{-n^2} g \sum_{k=0}^{\infty} \frac{1}{(k!)^2} \left(g^{-2k} \left(\sqrt{g}n\right)^{2k} * \left(\frac{\Gamma[1+2k]}{g} - \frac{1}{g^{3/2}\sqrt{\pi}} \left(2\Gamma\left[\frac{3}{2}+2k\right] \; 2F1\left[\frac{1}{2}, \frac{3}{2}+2k, \frac{3}{2}, -g\right] \right) \right) \right) \quad (23)$$

Back-substituting 'g' in eq. (23), we get the expression for BER in terms of 'n' and '$\bar{\gamma}$'. For any particular value of one these two parameters, the effect of variation of the other can be observed.

5. DECISION RULE BASED PERFORMANCE MODELING

For the performance analysis of a remote patient monitoring system under proposed model, we have taken Quadrature Phase Shift Keying (QPSK), a widely accepted modulation technique for wireless communication, to calculate the QoS parameters.

Bit Error Rate (BER) and Outage Probability for the link 1 (discussed in section II) are numerically calculated using expressions obtained in the previous section. For scenario (a) which is a complete indoor environment (described in section II), we initially assume the position of the patient such that there is a strong LOS path available between the on-body sensors and coordinator device. In this case, fig. 5 and fig. 6 present the plots of BER and Outage Probability vs. E_b/N_o using Nakagami-n. To represents presence of strong LOS component, we have taken n=7 where n is the ratio of LOS component to multipath component. For values of E_b/N_o above the threshold value of 5, the outage probability is almost zero. The BER also decreases as the value for E_b/N_o increases.

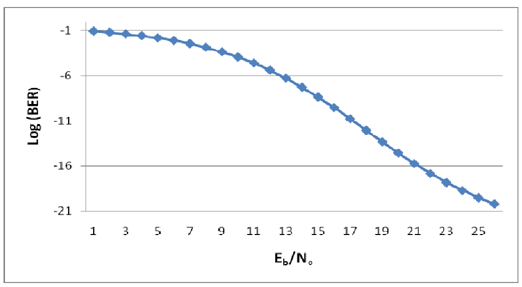


Figure 5: Bit Error Rate of QPSK for Nakagami-n channel model for various values of E_b/N_o taking n=7

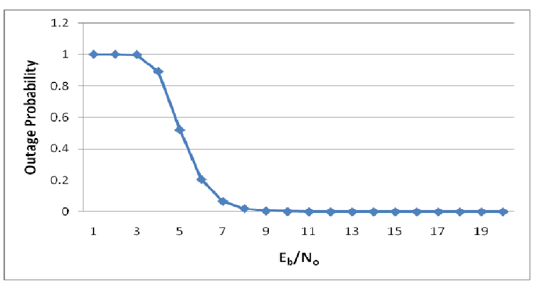


Figure 6: Outage Probability of QPSK for nakagami-n channel model for various values of E_b/N_o taking n=7 and γ_{th}=5

Now, as the patient moves inside the room or changes direction from the assumed initial position, the fraction of LOS component reduces as compared to multipath component. This change is represented by change in value of 'n' from initial assumed value of '7' towards '1'. The BER and outage probability also increase with reduction of LOS component as shown in fig. 7 and fig. 8 and finally matches with NLOS channel model which is best represented by Nakagami-m channel model for m=1. Fig. 8 gives a comparative study of BER for various values of 'n'. For n=1, BER distribution matches closely with Nakagami-m for m=1. Based on this plot, threshold values can be set for various values of E_b/N_o for a gradual change in the value of 'n' from LOS case to NLOS case. The two state adaptive model based on decision rule given by eq. (12) in section II can now be expanded to multiple states, each corresponding to a particular direction of the patient w. r. t. the coordinator device and modeled by a particular value of 'n'. For example, for a seven state model, various positions of the patient are quantized into 7 levels, each represented by a value of n from the set n_i = {1,7}.

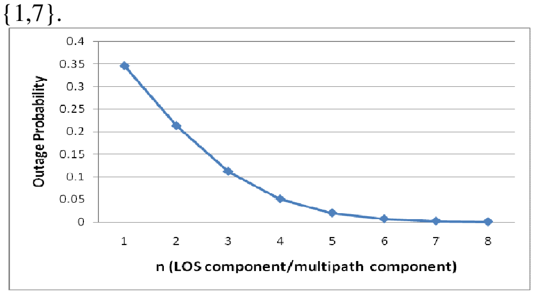


Figure 7: Outage probability of QPSK for various values of Nakagami-n channel model parameter 'n' taking γ_{th} =5 and avg. E_b/N_o=15.

From fig. 5, for E_b/N_o = 15, decision rule to select a particular value of n_i can be defined as:

$$n_i = \begin{cases} 7, & BER \le 2.897\text{E-}10 \\ 6, & 2.897\text{E-}10 < BER \le 3.046\text{E-}9 \\ : & \\ : & \\ 1, & 9.894\text{E-}4 < BER \le 0.0058 \end{cases} \tag{24}$$

The adaptive model can now be written as:

$$p_{N-n_i}(x) = 2de^{-n_i^2} x \exp(-dx^2) \sum_{k=o}^{\infty} \frac{(n_i x\sqrt{d})^{2k}}{(k!)^2} \tag{25}$$

Nakagami-n is a generalized case which leads to both NLOS (Rayleigh distribution) and LOS (Rice distribution) channel model for different values of 'n'. Using the proposed decision rule, we are able to achieve a more generalized or a better representation of the wireless fading channel model. The QoS parameters like outage probability and BER can now be estimated for almost all the positions and locations of the patient inside the room using this single model.

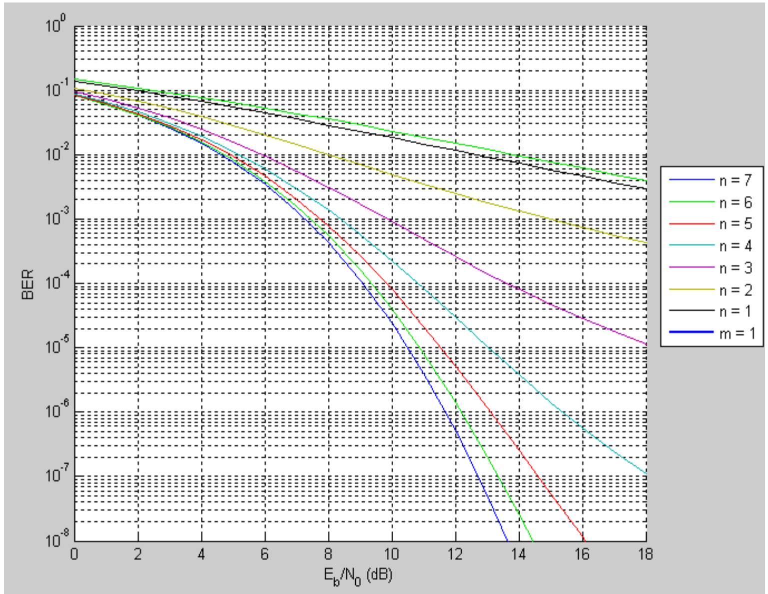


Figure 8: BER of QPSK for various values of n (Nakagami-n parameter) and for m=1 (Nakagami-m parameter)

6. CONCLUSION

In this paper, a novel way to mitigate channel diversity has been presented for the mission critical application of remote patient monitoring. A four state Markov model has been used to represent various channel conditions based on the location of the patient. An adaptive models and its QoS parameter based decision rule has been proposed for the indoor channel in context to this application. The objective is to capture the highly dynamic and random conditions of location of patients and healthcare professionals. A generalized Nakagami-n model with a variable parameter has been shown to capture the entire variation in signal strength and other effects. The suitability of the proposed model is judged by obtaining the expressions for outage probability and BER estimate and has been used for the performance analysis of the wireless channel. A decision rule based on BER estimation has also been suggested selecting the value of variable parameter 'n_i'.

Future work will focus on applying the proposed technique to clinical RF data, and to extending the approximations to also estimate other channel characteristics.

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