Packet Size Optimization for Improving the Energy Efficiency in Body Sensor Networks

Mari Carmen Domingo

Energy consumption is a key issue in body sensor networks (BSNs) since energy-constrained sensors monitor the vital signs of human beings in healthcare applications. In this paper, packet size optimization for BSNs has been analyzed to improve the efficiency of energy consumption. Existing studies on packet size optimization in wireless sensor networks cannot be applied to BSNs because the different operational characteristics of nodes and the channel effects of in-body and on-body propagation cannot be captured. In this paper, automatic repeat request (ARQ), forward error correction (FEC) block codes, and FEC convolutional codes have been analyzed regarding their energy efficiency. The hop-length extension technique has been applied to improve this metric with FEC block codes. The theoretical analysis and the numerical evaluations reveal that exploiting FEC schemes improves the energy efficiency, increases the optimal payload packet size, and extends the hop length for all scenarios for in-body and on-body propagation.

Keywords: Body sensor networks, packet size optimization, energy efficiency, ARQ, FEC block codes, FEC convolutional codes.

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I. Introduction

A body sensor network (BSN) is a radio frequency-based wireless networking technology that interconnects tiny nodes with sensor or actuator capabilities in, on, or around a human body [1]. We distinguish between implant and body surface nodes. Implant nodes are placed inside the human body, immediately below the skin or further deeper inside the body issue. Body surface nodes are placed on the surface of the human skin or at most two centimeters away from the body. Applications of BSNs are closely related to the healthcare domain, especially for continuous monitoring and logging vital parameters of patients suffering from chronic diseases. Based on implant and body surface devices, the following applications have been developed. First, BSNs may be used in implantable devices, such as pacemakers, implantable cardiac defibrillators (ICDs), implantable insulin pumps, and bladder control devices. Second, BSNs may be used in body surface devices, such as physiological sensors able to measure blood pressure, glucose monitoring, body temperature, blood oxygen, signals related to respiratory inductive plethysmography (RIP), and electroencephalography (EEG) [2].

This technology also enables the implementation of sports, military, or security applications.

Although BSNs have a similar architecture to wireless sensor networks (WSNs), a smaller scale and a different type and frequency are required for human body monitoring [3]. Since WSNs are not ideally suited for this purpose, specific BSNs should be developed. In addition, BSN and WSN nodes have different operational characteristics, such as sensing, signal processing, communication, storage, feedback control, and energy harvesting [2]. Communication in BSNs is challenged by human movements or posture changes in a time varying and sometimes highly dynamic environment. Body shadowing [2] appears when some propagation directions between the transmitting and receiving antennas are obstructed.

Energy consumption is a fundamental issue in BSNs since energy-constrained sensors monitor the vital signs of human beings in healthcare applications. Therefore, BSNs must operate properly and autonomously for long periods of time without battery recharge or replacement [4]. Advances in increased battery duration, power scavenging, and reduced energy consumption are eagerly awaited, especially regarding implantable sensors [3].

In this paper, packet size optimization for BSNs has been analyzed to improve the efficiency of energy consumption. Existing studies on packet size optimization in sensor networks cannot be applied to BSNs because the different operational characteristics of BSN nodes (sensing, signal processing, communication, storage, feedback control, and energy harvesting) [2] and the channel effects of in-body and on-body propagation are not considered. Automatic repeat request (ARQ), forward error correction (FEC) block codes named Bose, Ray-Chaudhuri, and Hocquenghem (BCH) and Reed-Solomon (RS), and FEC convolutional codes have been investigated regarding their energy efficiency. The hop-length extension technique has been applied to improve this metric with FEC block codes. Hop-length extension means that for the same transmission power, FEC block codes can reach longer distances by increasing the transmission ranges. Different scenarios for in-body and on-body propagation have been considered. To the best of our knowledge, this is the first paper that analyzes packet size optimization in BSNs based on the energy efficiency and examines the effects of error control schemes under different propagation phenomena on this metric. The theoretical analysis and the numerical evaluations reveal that exploiting FEC schemes improves the energy efficiency, increases the optimal payload packet size, and extends the hop length for all scenarios and propagation types in BSNs.

The paper is structured as follows. In section II, we discuss the related work on packet size optimization and error control schemes. In section III, we analyze our system model. In section IV, the channel model for BSNs is described. In section V, the energy consumption, the expressions of the energy efficiency, and the optimal packet size for each error control scheme are derived. In section VI, our numerical results are shown. Finally, the paper is concluded in section VII.

II. Related Work

Packet size optimization has been analyzed in WSNs. In [5], the optimal packet size that maximizes the energy efficiency is determined for different error control schemes in WSNs. In [6], packet size optimization has been analyzed for wireless terrestrial, underwater, and underground sensor networks. In [7], the impact of error control schemes on end-to-end energy consumption and latency has been studied for multihop sensor networks. However, all these analyses cannot be applied to BSNs due to the different operational characteristics of BSN nodes [2] and the channel effects of in-body [8] and on-body propagation [9]. The structure of the human body is complex and consists of different tissues, each with its own permittivity and conductivity. The different shape and proportions of fat and muscles of each human body is time-varying and affects electromagnetic propagation. Propagation depends also on the type of antennas and their position as well as on the body postures and movement. In addition, the channel characteristics for in-body and on-body sensor networks are different [8], [9]. In in-body sensor networks, signals propagate inside the human body and are affected by the body's electrical properties. In on-body sensor networks, the resulting signal is a combination of surface waves, creeping waves, diffracted waves, scattered waves, and free space propagation [10]. In our paper, different scenarios for in-body and on-body propagation have been considered.

Furthermore, in [7], the effects of the error controls schemes are analyzed for multihop communication. In [6], the optimal packet size for different objective functions such as energy consumption has also been found in multihop WSNs. In our paper, we analyze the effects of the error controls schemes for single-hop communication since this is the transmission type typical for BSNs. Besides, in [6] and [7], only ARQ and FEC block codes are considered. In our paper, convolutional codes have also been analyzed.

Error control techniques have been studied in BSNs. The benefits of combining ARQ with listen before talk (LBT) to improve the network performance are shown in [11]. The throughput and packet error rate have been analyzed in [12] with RS (63,55) as Reed-Solomon code and burst errors. However, in these works the effects of these error control schemes on the energy efficiency have not been studied. In our paper, we analyze and compare ARQ, FEC block, and FEC convolutional codes in terms of the energy efficiency.

III. System Model Analysis

We consider a BSN for healthcare monitoring (Fig. 1). In this architecture, implant or body surface sensors are used to monitor the physiological states of a person and transmit them towards a gateway located at the body surface using single-hop communication. Finally, the gateway transmits this data to a monitoring station, which forwards it towards the Internet.

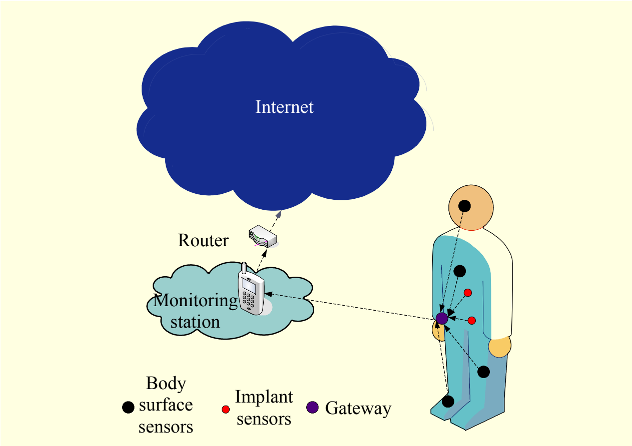

Fig. 1. Architecture for body sensor network.

IV. Channel Model

Propagation paths in BSNs can experience small and large scale fading. Small scale fading refers to the rapid changes of the amplitude and the phase of the received signal within a small local area due to small changes in the location of the on-body device or body positions in a given short period of time [8]. Small-scale fading is caused by the constructive and destructive interference of the multipath components at the receiver [13] (for instance, reflections from objects nearby can change the multipath profile for an ultra-wide band (UWB) body channel). Large scale fading or shadowing refers to variations of the received power due to obstruction of the propagation paths [13]. We distinguish between the shadowing caused by i) the body movements (changing postures, such as bending or rolling over in bed) and/or movement of the antennas with respect to the body and shadowing caused by ii) the surrounding objects when the antennas are positioned in the body and are in an external node (for example, when a person moves to a different location in the same room).

We assume that different measurements are carried out when the transmitter and receiver antennas on the body are moved to specific locations. Later on, the same measurements with the same locations for the antennas are repeated, but this time the person carrying the BSN changes his/her location in the room. At each antenna position in the body and at each location in the room, the attenuation is averaged over the different measurements to yield the large-scale path loss variations. This averaging mostly removes the effect of small-scale fading due to small changes in the user position around the room.

The average path loss between the transmitting and the receiving antennas is usually expressed by [8]

$$PL(d) = PL_0 + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\sigma, \tag{1}$$

where PL_0 is the path loss at a reference distance d_0, n is the path loss exponent, and X_σ is the shadowing component, which is a Gaussian-distributed random variable with zero mean and standard deviation σ in dB, that is, $X_\sigma \sim N(0,\sigma^2)$.

Three different scenarios are considered:

1. In-body communication between an implant sensor and the gateway,
2. On-body communication between a body surface sensor and the gateway (line-of-sight (LOS) channel),
3. On-body communication between a body surface sensor and the gateway (non-line-of sight (NLOS) channel).

In LOS propagation, electromagnetic waves travel in a straight line, whereas in NLOS propagation, radio transmission across a path is partially obstructed, for example, when waves propagate in the communication between back and torso.

An in-body channel model and on-body channel models (both LOS propagation and NLOS propagation) are used for the first, second, and third scenarios, respectively. The parameter values for each channel model have been obtained from [8], [14], and [15] for the first, second, and third scenarios, respectively. They are listed in Table 1 of section VI.

The received power at a distance d from the transmitter is

$$P_R(d) = P_T - PL(d), \tag{2}$$

where P_T is the transmission power in dBm.

Moreover, the signal to noise ratio (SNR) at the receiver is

$$\psi(d) = P_R(d) - P_n, \tag{3}$$

where P_n is the noise power in dBm.

Next, we derive the expressions for bit error rate (BER) and packet error rate (PER) for the error control schemes. The modulation schemes have been selected: on-off keying (OOK) due to its low-power operation and binary phase shift keying (BPSK) due to its BER improvement [16].

The BER for OOK is given by

$$p_b^{OOK} = \frac{1}{2} erfc\left(\sqrt{\frac{1}{4}\frac{E_b}{N_0}}\right), \quad E_b / N_0 = \psi \frac{B_N}{v_{TX}}, \tag{4}$$

where $\psi = 10^{\psi dB(d,f)/10}$, B_N is the noise bandwidth, and v_{TX} is the data rate.

The BER for BPSK is given by

$$p_b^{BPSK} = \frac{1}{2} erfc\left(\sqrt{\frac{E_b}{N_0}}\right), \quad E_b / N_0 = \psi \frac{B_N}{v_{TX}}. \tag{5}$$

Based on the bit error rate p_b, the PER for the error control schemes can be calculated as follows.

For ARQ, the CRC block code detection mechanism is deployed. Assuming detection of all packet errors, the PER of a single transmission for a packet of q bits is computed as

$$PER^{\text{CRC}}(q) = 1-(1-p_{\text{b}})^{q}. \tag{6}$$

BCH and RS FEC block codes are represented by (n, k, t), where n is the block length, k is the payload length, and t is the error correcting capability in bits. For BCH and RS codes, the block error rate (BLER) is given by

$$BLER(n,k,t) = \sum_{i=t+1}^{n} \binom{n}{i} p_{\text{b}}^{i} (1-p_{\text{b}})^{n-i}. \tag{7}$$

Since a packet can be larger than the block length n, the PER for BCH and RS block codes is given by

$$PER^{\text{BC}}(q,n,k,t) = 1-(1-BLER(n,k,t))^{\left\lceil \frac{q}{k} \right\rceil}, \tag{8}$$

where $\lceil q/k \rceil$ is the number of blocks required to send q bits.

For FEC convolutional codes, the PER of a single transmission for a packet of q bits is given by

$$PER^{\text{conv}}(q,n,k) = 1-(1-p_{\text{b}})^{\left\lceil \frac{q}{R_{\text{c}}} \right\rceil}, \tag{9}$$

where p_{b} is the bit error probability of an encoded data packet of length $\lceil q/R_{\text{c}} \rceil$ and code rate $R_{\text{c}} = k/n$.

V. Packet Size Optimization

In this section, the energy consumption is analyzed and the expressions of the energy efficiency and optimal packet size for each error control scheme are derived.

1. Energy Analysis

We are interested in analyzing the energy consumed when a sensor node i in a BSN sends data towards the gateway j using single-hop communication. The energy consumed is

$$E_{\text{comm}} = E_{\text{TX}} + E_{\text{RX}}, \tag{10}$$

where E_{TX} is the energy consumed by the transmitter (node i), and E_{RX} is the energy consumed by the receiver (node j).

For a successful packet transmission with ARQ, a node needs to receive an ACK. E_{TX} is given for ARQ as

$$E_{\text{TX}}^{\text{ARQ}} = E_{\text{TX, D}} + E_{\text{RX, A}}, \tag{11}$$

where $E_{\text{TX},u}$ is the packet transmission energy, D and A refer to DATA and ACK packets, respectively.

We use a simple energy consumption model [17]. $E_{\text{TX},u}$ can be computed as

$$E_{\text{TX},\ u} = E_{\text{TX-elec}} \cdot u + \frac{P_T}{v_{\text{TX}}} \cdot u, \tag{12}$$

where $E_{\text{TX-elec}}$ refers to the energy per bit needed by transmitter electronics and digital processing, P_{T} refers to the output transmit power (amount of energy spent in the RF amplifier), v_{TX} refers to the data rate, and u refers to the transmitted packet size. For ARQ, u refers to the data unit length.

$E_{\text{RX},u}$ can be computed as

$$E_{\text{RX},\ u} = E_{\text{RX-elec}} \cdot u, \tag{13}$$

where $E_{\text{RX-elec}}$ refers to the energy per bit needed by the receiver electronics.

E_{TX} is given for FEC as

$$E_{\text{TX}}^{\text{FEC}} = E_{\text{TX, D}}. \tag{14}$$

$E_{\text{TX, D}}$ is computed using (12) for FEC block codes and for FEC convolutional codes. A block code is represented by (n, k, t), where n is the block length, k is the payload length, and t is the error correcting capability in bits. Accordingly, the packet size u for block codes in (12) should be $\lceil (q/k)\cdot n \rceil$, where q refers to the data unit length, and $\lceil . \rceil$ is the ceiling function. Convolutional codes are represented by (n, k, m), where n is the number of output bits, k is the number of input bits, and m is the number of memory registers. Accordingly, u in (12) should be $\lceil q/R_{\text{c}} \rceil$, where R_{c} refers to the code rate, and is given by $R_{\text{c}} = k/n$.

Using the same approach, the energy consumption of the receiver mode E_{RX} is given as follows for ARQ and FEC:

$$E_{\text{RX}}^{\text{ARQ}} = E_{\text{RX, D}} + E_{\text{TX, A}}, \tag{15}$$

$$E_{\text{RX}}^{\text{FEC}} = E_{\text{RX, D}} + E_{\text{DEC, D}}, \tag{16}$$

where $E_{\text{DEC, D}}$ is the energy consumption of decoding for a FEC block code with length n and a t error correcting capability. It is given by [5]

$$E_{\text{DEC, BC}} = (2nt + 2t^2)(E_{\text{add}} + E_{\text{mult}}), \tag{17}$$

where E_{add} and E_{mult} are the energy consumption for addition and multiplication, respectively, of field elements in the Galois field $GF(2^m)$, $m = \lfloor \log_2 n + 1 \rfloor$. Therefore, in (16), the decoding energy for a data unit, $E_{\text{DEC,D}}$, is given by $E_{\text{DEC,D}} = E_{\text{DEC,BC}} \cdot \lceil q/k \rceil$. The energy consumption of decoding for a FEC convolutional code can be computed according to [17].

2. Energy Efficiency for In-Body Sensor Networks

Next, the energy efficiency with the different error control schemes for in-body sensor networks is introduced.

A. Energy Efficiency with ARQ

The energy efficiency represents the useful fraction of the total energy consumption in a communication link between sensors.

For ARQ, the CRC block code detection mechanism is deployed. Equations (12) and (13) can be rewritten for a transmitted packet as

$$\begin{aligned} E_{\mathrm{TX,\ D}} + E_{\mathrm{RX,\ D}} &= \left(E_{\mathrm{RX\text{-}elec}} + E_{\mathrm{TX\text{-}elec}} + \frac{P_{\mathrm{T}}}{v_{\mathrm{TX}}} \right) \cdot (h+s) \\ &= x \cdot (h+s), \end{aligned} \tag{18}$$

where s refers to the payload length, and h refers to the header length of the transmitted packet.

The energy efficiency with ARQ can be defined as

$$\mu = (1 - PER) \cdot \frac{x \cdot s}{x \cdot (h+s) + E_{\mathrm{RX,\ A}} + E_{\mathrm{TX,\ A}}}, \tag{19}$$

where PER is given by (6).

Our task is to maximize μ with respect to the payload length. It can be shown that there exists a maximum for the optimization function. The optimal payload size for ARQ is

$$s_{\mathrm{opt}}^{\mathrm{ARQ}} = -\frac{1}{2} f + \sqrt{f^2 - \frac{4f}{\ln(1 - p_{\mathrm{b}})}}, \tag{20}$$

where $f = h + \dfrac{E_{\mathrm{RX,\ A}} + E_{\mathrm{TX,\ A}}}{x}$.

B. Energy Efficiency with FEC Block Codes

The energy efficiency with FEC block codes is defined as

$$\delta = (1 - PER) \cdot \frac{x \cdot \left\lceil \frac{s}{k} \cdot n \right\rceil}{x \cdot \left\lceil \frac{(h+s)}{k} \cdot n \right\rceil + E_{\mathrm{DEC,\ D}}}, \tag{21}$$

where PER is given by (7) and (8). The denominator of (21) represents the total energy consumption for a transmitted packet (each packet is divided into $(h + s)/k$ blocks of length n). The whole packet $(h + s)$ is considered. The numerator of (21) represents the useful energy, that is, the energy spent to send and receive the useful part of the packet (s) as a group of $(h+s)/k$ blocks of length n when these bits are correctly received. The numerator is multiplied by (1 – PER), which represents the reliability that the packet is properly received.

The optimal payload length for FEC block codes that maximizes the energy efficiency is

$$s_{\mathrm{opt}}^{\mathrm{BC}} = -\frac{1}{2} f + \sqrt{f^2 - \frac{4fk}{\ln(1 - BLER)}}, \tag{22}$$

where $f = h + \dfrac{E_{\mathrm{DEC,\ D}}}{x} \cdot \left\lceil \dfrac{k}{n} \right\rceil$ and the BLER is given by (7).

C. Energy Efficiency with FEC Convolutional Codes

The energy efficiency with FEC convolutional codes is

$$\alpha = (1 - PER) \cdot \frac{x \cdot \left\lceil \frac{s}{R_{\mathrm{c}}} \right\rceil}{x \cdot \left\lceil \frac{s+h}{R_{\mathrm{c}}} \right\rceil + E_{\mathrm{DEC,\ D}}}, \tag{23}$$

where the PER is given by (9).

The optimal payload length for FEC convolutional codes that maximizes the energy efficiency is

$$s_{\mathrm{opt}}^{\mathrm{CC}} = -\frac{1}{2} f + \sqrt{f^2 - \frac{4fR_{\mathrm{c}}}{\ln(1 - p_{\mathrm{b}})}}, \tag{24}$$

where $f = h + \dfrac{R_{\mathrm{c}} \cdot E_{\mathrm{DEC,\ D}}}{x}$.

3. Energy Efficiency for On-Body Sensor Networks

Next, energy efficiency with different error control schemes for on-body sensor networks is introduced. In on-body sensor networks, the fading envelope changes continuously in accordance with body motion. In mobile body sensor networks, the normalized Doppler bandwidth is small; therefore, the fading process is highly correlated causing burst errors that can last for tens or even hundreds of milliseconds. In this case, FEC codes would not be efficient. The probability of correct packet transmission in fading channels depends on the number of fades during the transmission time, burst-error duration, and error-correcting capability of channel coding. Therefore, in order to determine the energy efficiency with ARQ, FEC block codes or FEC convolutional codes, equations (19), (21), and (23) should be multiplied by the probability of correct packet transmission in fading channels p_s, which is given by [18]:

$$p_s = e^{-\frac{T}{t_{\mathrm{if\_avrg}}}} - \left(\frac{T}{t_{\mathrm{if\_avrg}}} \right) E_1 \left(\frac{T}{t_{\mathrm{if\_avrg}}} \right), \tag{25}$$

where $E_1(y) = \int_y^{\infty} e^{-t} t^{-1} dt$. $t_{\mathrm{if\_avrg}}$ refers to the mean of the interfade duration (the period of time between two successive fades), and T refers to the transmission time of the packet.

VI. Results

We study the performance of ARQ and FEC codes with respect to the energy efficiency in BSNs via numerical evaluations.

We analyze the effects of the proposed techniques for in-body and on-body sensor networks. The channel models

Table 1. Parameter values.

Parameter	Value	
Overhead size	80 bits	
ACK size	8 bytes	
Transmission power P_T	In-body: –10 dBm On-body: –12 dBm	
Noise power P_n	–100 dBm	
Channel model implant (near surface) to gateway for f: 402 to 405 MHz	d_0: 5 cm	
	PL_0: 49.81 dB	
	n: 4.22	
	σ_S: 6.81 dB	
Channel model body surface to gateway	LOS	NLOS
	f = 2.45 GHz	f = 3.1 GHz
	d_0: 10 cm	d_0: 10 cm
	PL_0: 35.2 dB	PL_0: 48.4 dB
	n: 3.11	n: 5.9
	σ_S: 6.1 dB	σ_S: 5.0 dB
Data rate	In-body: 800 kbps On-body: 2 Mbps	
$E_{TX\text{-}elec}$	In-body: 18.75 nJ/bit On-body: 11.25 nJ/bit	
$E_{RX\text{-}elec}$	In-body: 18.75 nJ/bit On-body: 11.25 nJ/bit	
E_{add}	$3.3\times10^{-14}m$ W/Hz, where $m=\lfloor \log_2 n+1 \rfloor$	
E_{mult}	$3.7\times10^{-14}m^3$ W/Hz, where $m=\lfloor \log_2 n+1 \rfloor$	

considered appear in section IV. The parameters used in our evaluation are listed in Table 1. They follow the architecture of the Zarlink ZL70101 [19] and the Nordic nRF24L01+ [20] ultra-low power chip transceivers for in-body and on-body sensor networks, respectively. We use as FEC block codes the BCH codes BCH (127, 8, 31), BCH (127, 125, 1), BCH (127, 120, 1), BCH (127, 120, 10), BCH (127, 120, 5), BCH (127, 15, 27), BCH (127, 22, 23), BCH (31, 11, 5), BCH (31, 11, 15), BCH (31, 21, 5), and the RS code RS (63, 55, 4). They are shortened codes with mother codes BCH (152, 33, 31), BCH (152, 150, 1), BCH (152, 145, 1), BCH (152, 145, 10), BCH (152, 145, 5), BCH (152, 40, 27), BCH (152, 47, 23), BCH (56, 36, 5), BCH (56, 36, 15), BCH (56, 46, 5), and RS (79, 65, 7), respectively. We use a FEC convolutional code with code rate 1/2. However, other FEC schemes could also be used in our framework yielding similar performance. Our numerical results for a mobile wireless on-body sensor network with a relative body movement velocity of 3.5 km/h show a resulting average fade duration of 75.1 ms and an

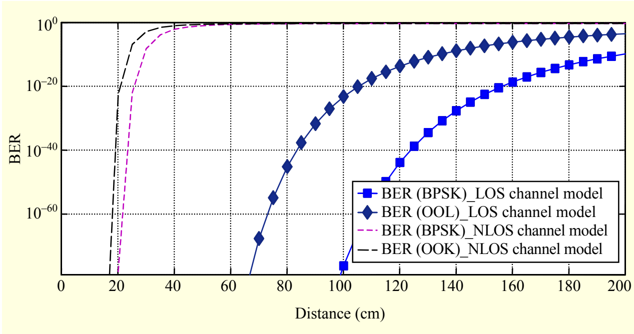

Fig. 2. BER vs. distance for on-body sensor networks (LOS and NLOS channel models).

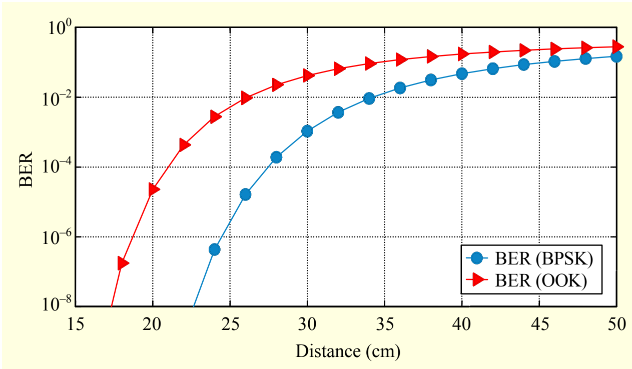

Fig. 3. BER vs. distance for in-body sensor networks.

average interface duration of 46.7 ms.

1. Bit Error Rate

We analyze the effects of different modulation schemes on the BER for on-body and in-body sensor networks. In Fig. 2 the BER is shown as a function of the distance between the body surface node and the gateway for the BPSK and OOK modulations (on-body sensor network). Different curves for the LOS and NLOS channel models have been depicted assuming the validity of the models at these distances. The NLOS channel model supports lower hop-length extensions than the LOS channel model because the path loss is higher as the path is partially obstructed, for example, when waves propagate in the communication between the back and torso. For a particular BER, the hop length is extended more using the BPSK than the OOK modulation for both channel models. For a particular hop distance, the BER is lower for BPSK than for OOK modulation (LOS or NLOS propagation). For instance, for a distance of 40 cm, the BER is 92.7% lower for the BPSK than for the OOK modulation with the NLOS channel model.

In Fig. 3, the BER is shown as a function of the distance between the implant node and the gateway for the BPSK and OOK modulations (in-body sensor network). Again, the BPSK modulation results in larger hop-length extension than OOK. For a target BER of 10^{-3}, the hop length is extended to 30.4% using BPSK instead of OOK modulation.

2. Payload Length

We investigate the effects of packet size optimization on the energy efficiency for the error control schemes. In Fig. 4 and Fig. 5, the energy efficiency for an in-body and on-body sensor network, respectively, are shown as a function of the payload length for ARQ and the convolutional code with R_c=1/2. The BER values are 10^{-3} and 10^{-5}. The energy efficiency is lower and decays faster with the increase of the payload length for on-body than for in-body sensor networks due to the continuous change of fading envelope. The optimal payload length for in-body and on-body sensor networks with respect to different BER values is shown in Table 2. The payload length values are smaller for on-body sensor networks because, as the packet size (and packet time duration) is longer, the probability that the packet falls in the faded duration is larger. In Figs. 4 and 5, the energy efficiency and the optimal payload length increase with decreasing BER. With ARQ and the convolutional code with R_c=1/2 for a payload length of 1,000 bits, the energy efficiency is 65.7% and 88.2% lower for a BER of 10^{-3} in comparison with a BER of 10^{-5}, respectively (in-body sensor network). For ARQ and the convolutional code with R_c=1/2, the optimal payload length (in-body sensor network) is 91.6% and 91.7% lower for a BER of 10^{-3} compared to a BER of 10^{-5}, respectively. For the convolutional code with R_c=1/2, the optimal payload length (on-body sensor network) is 79.5% lower for a BER of 10^{-3} compared to a BER of 10^{-5}.

For a given BER, the energy efficiency drops abruptly for payloads smaller than the optimal length due to the higher overhead of smaller packets. This effect is especially noticeable in the case of ARQ. However, the energy efficiency decreases slowly for payloads larger than the optimal length. This effect is more perceptible for in-body sensor networks, lower bit error rates (better channel conditions), and in the case of ARQ. Therefore, we conclude that with payloads significantly higher than the optimal payload length, still near-optimal energy efficiency can be obtained. The optimal payload length in an in-body sensor network is 44.3% (46.6% in an on-body sensor network) lower for the convolutional code with R_c=1/2 compared to ARQ and a BER of 10^{-3}. Convolutional codes show the worst performance compared to ARQ since their optimal payload sizes are significantly smaller, and the energy efficiency decreases more quickly for payloads larger than the optimal length. The energy efficiency and the payload length increase with an increasing code rate. Convolutional codes with a low code rate have higher PER, which affects energy efficiency.

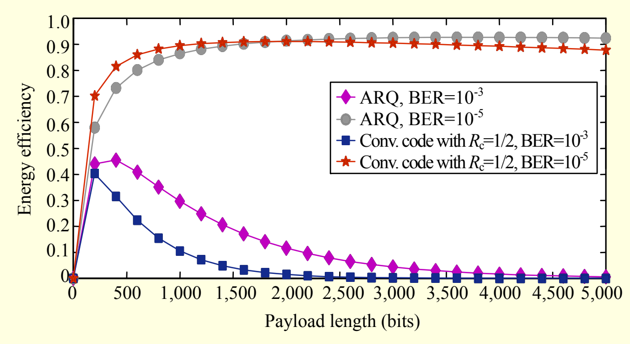

Fig. 4. Energy efficiency vs. payload length in in-body sensor network for ARQ and convolutional codes.

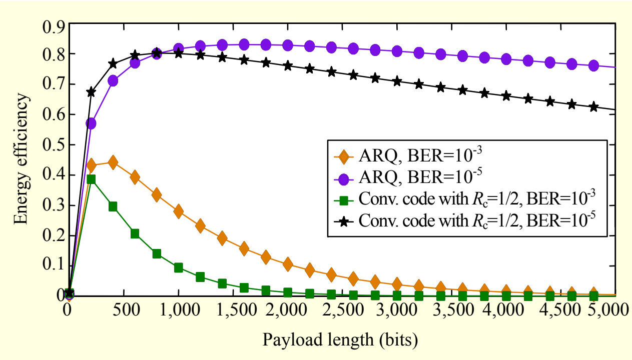

Fig. 5. Energy efficiency vs. payload length in on-body sensor network for ARQ and convolutional codes.

Table 2. Optimal payload length for ARQ and FEC convolutional codes.

BER	Optimal payload length (bits)			
	ARQ		FEC conv. code with R_c=1/2	
	In-body	On-body	In-body	On-body
10^{-3}	314	307	175	164
10^{-4}	1,130	1,001	639	401
10^{-5}	3,723	1,601	2,117	801

In Figs. 6 and 7, the energy efficiency for an in-body and an on-body sensor network, respectively, are shown as a function of the packet payload length for FEC block codes. The optimal packet payload lengths for BCH (127, 125, 1) and BCH (127, 120, 1) for in-body and on-body sensor networks with respect to different BER values are illustrated in Table 3. Again, the energy efficiency and the optimal packet payload size increase with decreasing BER.

FEC block codes can achieve better energy efficiencies in

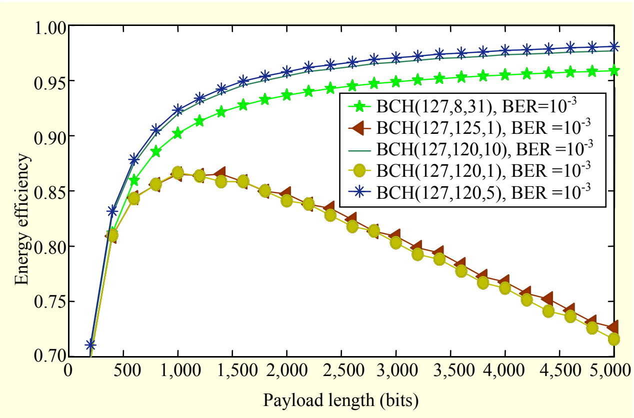

Fig. 6. Energy efficiency vs. payload length in in-body sensor network for FEC block codes.

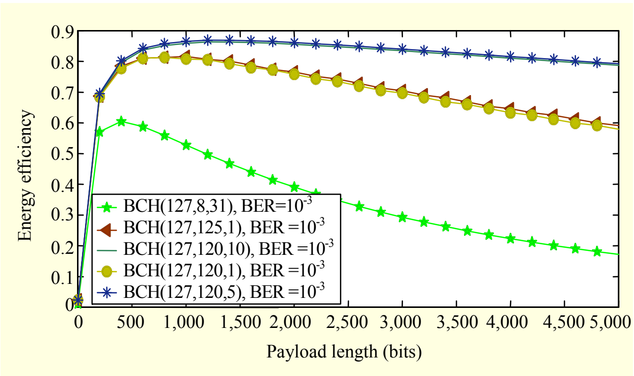

Fig. 7. Energy efficiency vs. payload length in on-body sensor network for FEC block codes.

Table 3. Optimal payload length for FEC block codes.

BER	Optimal payload length (bits)			
	FEC block code BCH (127, 125, 1)		FEC block code BCH (127, 120, 1)	
	In-body	On-body	In-body	On-body
10^{-3}	1,133	1,001	1,110	801
10^{-4}	11,312	1,382	11,084	1,360
10^{-5}	1.13×10^{5}	1,396	1.11×10^{5}	1,374

comparison with the other error control schemes. For the same block length n and error correcting capability t, the energy efficiency and the optimal packet payload size increase with increasing payload length k of the block code because the PER is decreased. For an in-body sensor network with BCH (127, 125, 1), the optimal packet payload size is 1.8% larger compared to BCH (127, 120, 1) and a BER of 10^{-5}. For the same block length n and payload length k, when the error correcting capability t is increased, the PER of the code is decreased, but the energy consumption of decoding is increased. The tradeoff between both parameters (PER and energy consumption of decoding) affects the energy efficiency. For very low error correcting capabilities, the PER of the code is increased, but the energy consumption in decoding is decreased. In this case, the energy efficiency decreases because the increase in the PER prevails over the decrease in the energy consumption of decoding. Therefore, for BCH (127, 120, 1), the energy efficiency is 20.3% lower than with BCH (127, 120, 5) for a payload length of 3,600 bits and a BER of 10^{-3} (in-body sensor networks). For higher error correcting capabilities, the PER of the code is decreased, but the energy consumption in decoding is increased. In this case, the energy efficiency decreases because the increase in the energy consumption of decoding prevails over the decrease in the PER. Thus, for BCH (127, 120, 10), the energy efficiency is 0.39% lower than with BCH (127, 120, 5) for a payload length of 3,600 bits and a BER of 10^{-3} (in-body sensor networks). For the same error correcting capability t, when the block length n is decreased, the energy efficiency and the optimal packet payload size are improved because the PER as well as the energy consumption of decoding are decreased. The energy efficiency as well as the payload length values are lower for on-body compared to in-body sensor networks.

3. Hop-Length Extension

Next, we analyze how to extend the hop length between each sensor node and the gateway maintaining good energy efficiency. The energy efficiency as a function of the distance for a payload length of 2,000 bits is shown in Figs. 8, 9, and 10 for in-body sensor networks [8], on-body sensor networks (LOS channel model [14]), and on-body sensor networks (NLOS channel model [15]), respectively. At moderate hop distances, a payload size closer to the optimal payload is preferable since the energy efficiency is higher (Fig. 8). For a distance between the implant sensor inside the skin and the gateway of 14 mm, ARQ shows the best improvement when the payload length is modified. With a payload length of 2,000 bits, the energy efficiency is 31.7% higher than with a payload length of 350 bits. However, the energy efficiency is degraded more quickly for the payload of 2,000 bits as the distance is increased. On the contrary, for the payload size of 350 bits, the energy efficiency degradation is more gradual.

For in-body sensor networks, the energy efficiency with the ARQ scheme is the lowest. However, for on-body sensor networks (LOS and NLOS channel models), the energy efficiency with the convolutional code with R_c=1/2 is the lowest since the probability of correct transmission in fading channels is lower. With the convolutional code with R_c=1/2 and

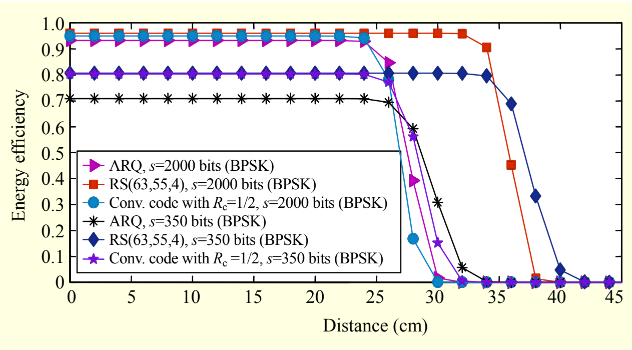

Fig. 8. Energy efficiency vs. distance for in-body sensor networks.

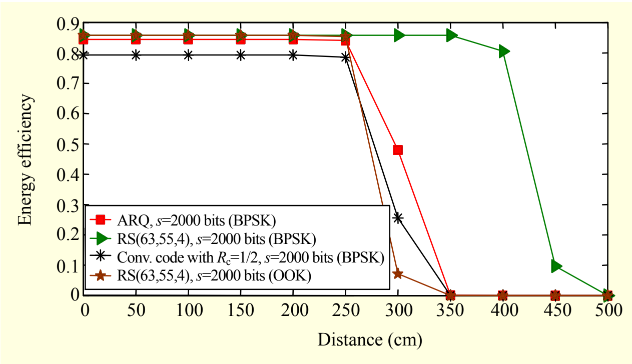

Fig. 9. Energy efficiency vs. distance for on-body sensor networks (LOS).

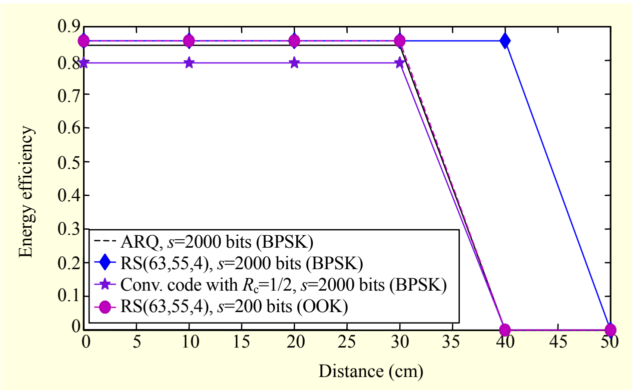

Fig. 10. Energy efficiency vs. distance for on-body sensor networks (NLOS).

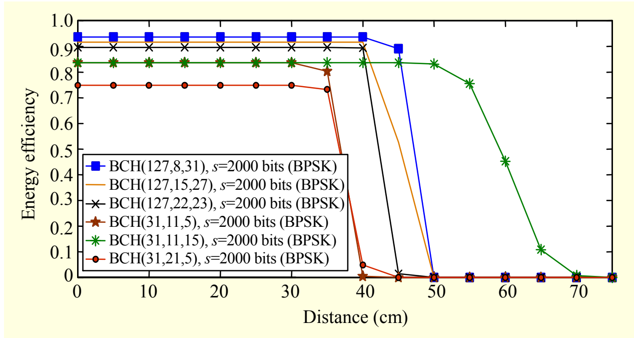

Fig. 11. Energy efficiency vs. distance for in-body sensor networks.

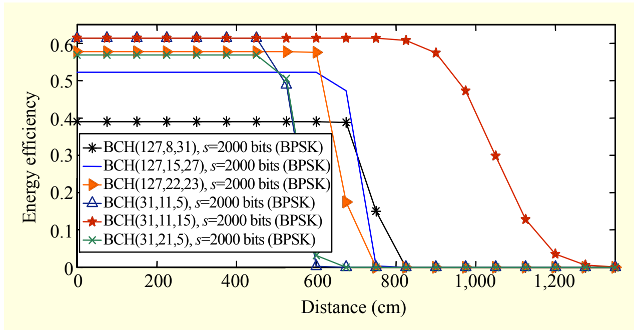

Fig. 12. Energy efficiency vs. distance for on-body sensor networks (LOS).

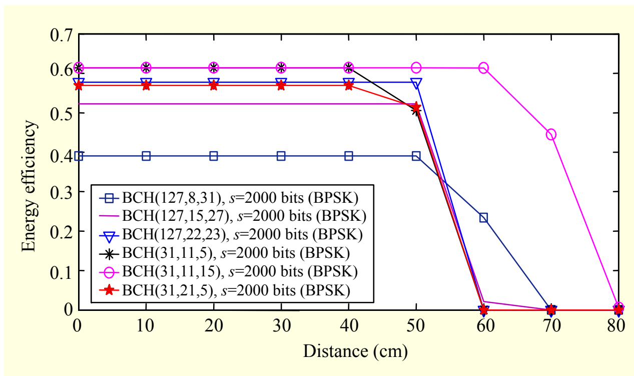

Fig. 13. Energy efficiency vs. distance for on-body sensor networks (NLOS).

a payload of 2000 bits, the energy efficiency is 7.6% and 6.2% lower than RS (63, 55, 4) and ARQ, respectively, for on-body sensor networks (LOS) with BPSK modulation and a distance between body surface sensor and gateway of 40 cm (Fig. 9).

FEC block codes are able to maintain high-energy efficiency values over longer distances because the hop-length extension technique is applied. This means that for the same transmission power, FEC block codes can reach longer distances (increase the transmission ranges). For an energy efficiency of 0.80 (good value), the hop length has been extended for RS (63, 55, 4) using a payload length of 2,000 bits and BPSK modulation to 35 cm for in-body sensor networks, to 400 cm for on-body sensor networks (LOS) (assuming the validity of the channel model at this distance), and to 41 cm for on-body sensor networks (NLOS). With FEC block codes and BPSK modulation, the hop length is extended more than with OOK modulation because the BER is lower, as shown in Figs. 2 and 3. For an energy efficiency of 0.8, the hop length for RS (63, 55, 4) with BPSK modulation is 56.9% and 28.1% larger in comparison with OOK modulation for the LOS and NLOS channel models (on-body communication), respectively, assuming the validity of the channel models at these distances.

Next, we study more carefully the relationship between the energy efficiency and the distance for FEC block codes since they result in higher extension of hop length. The energy efficiency is shown as a function of distance for in-body and on-body sensor networks (LOS and NLOS channel models) in Figs. 11, 12, and 13, respectively. For the same block length n and payload length k, the hop length is increased with the error correcting capability t of the code. For an energy efficiency of 0.4, the hop length is increased 64.9%, 83.6%, and 38.5% with BCH (31, 11, 15) compared to BCH (31, 11, 5) for in-body and on-body sensor networks (LOS and NLOS channel models), respectively. The energy efficiency is increased for the same code length n and error correcting capability t when the payload length k is decreased. For a distance between the sensor and the gateway of 30 cm, the energy efficiency is increased 11.8%, 7.9%, and again 7.9% with BCH (31, 11, 5) compared to BCH (31, 21, 5) for in-body and on-body sensor networks (LOS and NLOS), respectively. The energy efficiency for in-body sensor networks is decreased when the block length n for the different FEC block codes is reduced. The energy efficiency values for on-body sensor networks are affected by the probability of correct packet transmission in fading channels, which diminishes when the ratio n/k is increased. In this case, the transmission time of the packets is increased because the payload length for each block code is reduced. BCH (31, 11, 15) extends the hop length the most. It has been extended for an energy efficiency of 0.45 to 60 cm for in-body sensor networks, 985 cm for LOS channel on-body sensor networks, and 70 cm for NLOS channel on-body sensor networks. These measurements assume the validity of the channel models at these distances.

VII. Conclusion

In this paper, packet size optimization based on the energy efficiency has been analyzed. The error control schemes ARQ, FEC block codes, and FEC convolutional codes have been investigated regarding this metric. The energy efficiency and the optimal payload length increase with decreasing BER for all error control schemes. Since the energy efficiency decreases slowly for payloads larger than the optimal length, with these payloads still near-optimal energy efficiency can be obtained. FEC block codes can achieve better energy efficiency in comparison with the other error control schemes. Since for the same block length n and payload length k, with increasing error correcting capability t, the PER of the FEC block code is decreased but the energy consumption of decoding is increased, moderate values of t result in higher energy efficiency and good payload packet size. The results show that the optimal packet length to improve the energy efficiency depends on the type of BSN (in-body or on-body sensor network).

We have analyzed how to extend the hop length while maintaining good energy efficiency. At moderate hop distances, a payload size closer to the optimal is preferable since the energy efficiency is higher. For in-body sensor networks, the energy efficiency with the ARQ scheme is the lowest. However, for on-body sensor networks (LOS and NLOS channel models), the energy efficiency with the convolutional code with $R_c = 1/2$ is the lowest since the probability of correct transmission in fading channels is lower. With FEC block codes and BPSK modulation, the hop length is extended more than with OOK modulation because the BER is lower. FEC block codes are able to maintain high energy efficiency values over longer distances because the hop-length extension technique is applied. This means that for the same transmission power, FEC block codes can reach longer distances (increase the transmission ranges). We observe that for the same block length n and payload length k, the hop length is increased with the error correcting capability t of the code.

An interesting direction for future research lies in evaluating the energy efficiency for other BSN topologies different from the single-hop star topology discussed in the paper.

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