

Distributed Joint Source-Channel Coding with Raptor Codes for Correlated Data Gathering in Wireless Sensor Networks

[Invited]

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ABSTRACT

Correlated data gathering in body area networks calls for systems that perform efficient compression and reliable transmission of the measurements, while imposing a small computational burden at the sensors. Highly-efficient compression mechanisms, e.g., adaptive arithmetic entropy encoding, do not address the problem adequately, as they have high computational demands. In this paper, we propose a new distributed joint source-channel coding (DJSCC) solution for this problem. Following the principles of distributed source coding, our design allows for efficient compression and error-resilient transmission while exploiting the correlation amongst sensors' readings at energy-robust sink nodes. In this way, the computational complexity and in turn, the energy consumption at the sensor node is kept to a minimum. Our DJSCC design is based on a new non-systematic Slepian-Wolf Raptor code construction that achieves good performance at short code lengths, which are appropriate for low-rate data gathering within local or body area sensor networks. Experimental results using a WSN deployment for temperature monitoring reveal that, for lossless compression, the proposed system leads to a 30.08% rate reduction against a baseline system that performs adaptive arithmetic entropy encoding of the temperature readings. Moreover, under AWGN and Rayleigh fading channel losses, the proposed system leads to energy savings between 12.19% to 16.51% with respect to the baseline system.

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BODYNETS 2014, September 29-October 01, London, Great Britain

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DOI 10.4108/icst.bodynets.2014.257111

Categories and Subject Descriptors

H.1.1 [Coding and Information Theory]: Data compaction and compression, Error control codes

General Terms

Design, Algorithms, Performance

Keywords

Wireless sensor networks (WSNs), Distributed joint source-channel coding (DJSCC), Raptor Codes, Temperature monitoring.

1. INTRODUCTION

Wireless local area and body area networks (WLANs/WBANs) operate under austere constraints in terms of energy resources, computational capabilities and available bandwidth [10, 18, 32, 36]. WBAN applications, e.g., temperature monitoring [18, 27], wearable visual sensors [9] or in-body sensors [7], involve a number of sensors on/in or near the body, thereby sensors' readings are highly correlated. In order to increase the throughput and lifetime of the network, this correlation needs to be exploited by efficient data compression mechanisms that have low computational complexity [18, 29]. In addition, as information is sent over error-prone wireless channels, effective data protection schemes are required to provide for reliable communications.

Distributed source coding (DSC) is considered a key technology for wireless sensor networks (WSNs) [25, 34]. DSC designs exploit the correlation between the sensors' data at the decoder, that is, the collection (sink) node, without requiring inter-sensor communication. In this way, efficient compression is obtained by shifting the complexity to robust sink nodes, while keeping the sensor computational and energy demands to a minimum. Moreover, energy-consuming data exchange between sensors is avoided. This is in contrast to predictive coding systems, e.g., [27], which apply complex adaptive prediction and entropy coding at the en-

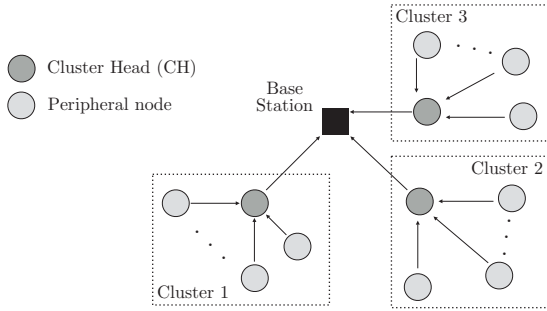


Figure 1: The cluster-based network architecture. The nodes measure environmental or body temperature.

coder. In addition, in order to remove the correlation among readings of neighboring sensors, predictive coding systems require the sensors to communicate. This has a major impact on the computational demands and transmission power consumption of the sensors.

Temperature sensors, being wearable (on-body), or located in the living environment of an individual, are key components of WLAN/WBAN systems for assisted living or health care monitoring [5, 18]. Several works have investigated DSC schemes for wireless sensors monitoring temperature, applicable to WBANs or WLANs. A simple coset construction realizing Slepian-Wolf (SW) coding for two sensors measuring the temperature in a room was devised in [23]. The scheme was extended to a cross-layer design by modeling the interaction between DSC and the medium access control (MAC) layer in [22]. Concerning lossy distributed compression, a code design comprising quantization followed by binarization and low-density parity-check (LDPC) encoding was proposed in [5]. Considering a multi-sensory scenario, Cheng [6] introduced a multiterminal code design in which SW coding was simply replaced by entropy coding, whereas joint source reconstruction at the decoder was realized by Gaussian process regression.

This paper proposes a novel distributed joint source-channel coding (DJSCC) design for WSNs measuring temperature. Contrary to contemporary schemes for temperature data encoding, e.g., [3–6, 20, 27], which focus only on data compression, our design *jointly* addresses compression and error-resilient transmission of data. In this way, channel impairments are mitigated without requiring packet retransmissions at the MAC layer, thereby leading to significant energy savings for each sensor node. We devise a novel scheme using asymmetric SW coding realized by Raptor codes [28]. Contrary to other SW constructions that are based on Turbo [1, 12] or LDPC [17, 30] codes, Raptor codes offer a flexible adaptation of the code rate, which is an asset in hands-on applications where inter-sensor correlations vary. Conversely to other designs (e.g., [11, 35]) that consider long codewords, our SW Raptor code design allows for good performance at short code lengths, which are particularly important for the temperature monitoring application. Experimental results using real data from a proprietary WSN deployment show that the proposed system introduces significant compression gains (up to 30.08% in rate reduction)

with respect to the baseline scheme that performs adaptive arithmetic entropy coding of the data. These coding gains lead to notable energy savings (up to 16.51%) at the sensor nodes with respect to the baseline system.

The remainder of the paper is as follows: Section 2 discusses the considered network model and the proposed architecture. Section 3 presents our DJSCC Raptor code design whereas, Section 4 elaborates on the statistical model for the correlation amongst the sensors' readings. Section 5 gives the experimental results and Section 6 concludes the work.

2. NETWORK MODEL AND PROPOSED SYSTEM

2.1 Network Model

We consider a WSN comprising sensor nodes monitoring the temperature in the environment of an individual, as well as wearable sensors that record the body temperature. The WSN is organized into *clusters*, each comprising an elected *cluster head* (CH) and *peripheral nodes* (see Figure 1). Peripheral nodes measure temperature data, apply compression and error protection mechanisms and transmit the resulting data packets to the base station via their corresponding CH. CHs are group coordinators that organize data transfer, sleeping periods and data aggregation, as well as transmit the processed data to the base station. In addition, each CH transmits its own temperature data. To prevent CH battery depletion, the CH changes periodically based on energy criteria [2, 26]. When the residual energy of the CH turns low, another CH is elected among the peripheral nodes. In this way, energy consumption is balanced within the cluster and the network lifetime increases [2, 26]. The cluster formation abides by well-known cluster-tree solutions for IEEE 802.15.4-based MAC protocols in WSNs, e.g., the IEEE 802.15.4 GTS [16]. Transmission is performed over the 16 channels of the IEEE 802.15.4 PHY and inter-sensor interference is mitigated via the utilized MAC layer cluster-tree coordination [16].

2.2 Proposed DJSCC Architecture

In the proposed architecture, shown in Figure 2, the temperature data gathered by the sensors in each cluster is encoded by means of SW coding. Each sensor acquires discrete temperature samples through an analog-to-digital converter with b bit-depth accuracy. Under the memory capabilities of the sensor, m samples are aggregated together for encoding. Binarization is performed by means of gray encoding¹ [13], resulting in an array of $k = m \times b$ bits to be encoded.

The binarized information of the CH is intra-encoded using adaptive arithmetic entropy coding, achieving a source coding rate of $R_{X_N} \geq kH(X_N)$ bits. The compressed bit-stream is then channel encoded resulting in the total transmitted information of $R'_{X_N} \geq k\frac{H(X_N)}{C}$ bits, where C denotes the channel capacity. Channel encoding is realized using Raptor codes that adhere to the systematic code described in the Raptor RFC5053 standard [19]. At the decoder, the

¹Gray encoding is used to enhance the performance of SW coding as in the former the binary representations of two consecutive values differ in one bit position.

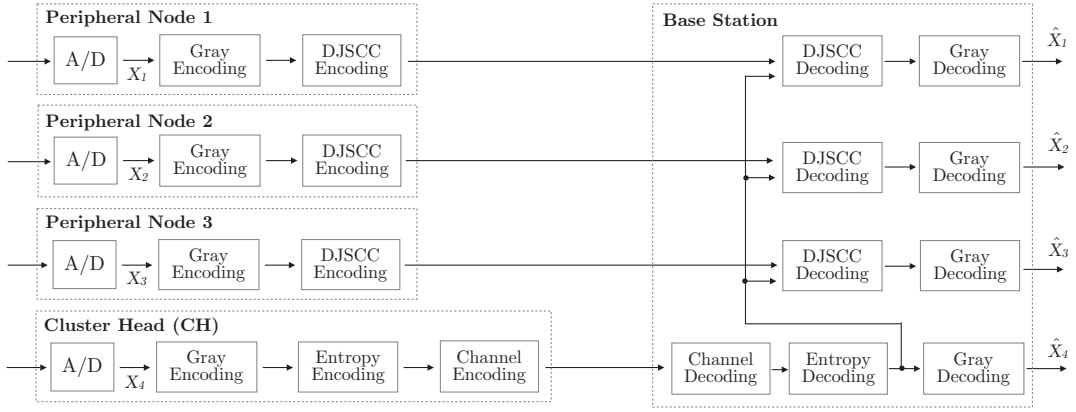


Figure 2: The proposed system architecture.

encoding operations are reversed resulting in the decoded CH data. The decoded CH data acts as side information to SW decode the data from the peripheral nodes.

Each of the peripheral nodes in the cluster encodes its data (denoted as X_1, \dots, X_{N-1}) using asymmetric SW coding as explained in the subsequent section.

3. DISTRIBUTED JOINT SOURCE-CHANNEL CODE DESIGN

Let $\mathbf{x}_n = [x_n(1), \dots, x_n(k)]$ be the k information bits of source X_n from a peripheral node $n = 1, 2, \dots, N-1$. DJSCC encoding is applied to \mathbf{x}_n , realized by a SW Raptor encoder. Based on the Raptor RFC5053 standard [19], which defines a systematic channel code, we design a non-systematic code construction for SW coding.

The Tanner graph of the designed non-systematic Raptor SW code in depicted in Figure 3. At the encoder, the LDPC codeword is first formed as $\mathbf{y}^T = \mathbf{G}_{\text{LDPC}_{w \times k}} \times \mathbf{x}^T$, where $w = k + s$ and $\mathbf{G}_{\text{LDPC}_{w \times k}}$ is the generator matrix of the LDPC precode. Then, the Raptor codeword is given by $\mathbf{c}^T = \mathbf{G}_{\text{LT}_{p \times w}} \times \mathbf{y}^T$, where $\mathbf{G}_{\text{LT}_{p \times w}}$ is the generator matrix of the Luby Transform (LT) code. The $R_{X_n} = p$ bits from the output of the non-systematic encoder are transmitted. When noiseless transmission is considered then, for decoding with low error probability, we need that $R_{X_n} = p \geq kH(X_n|X_N)$ bits. The conditional entropy $H(X_n|X_N)$ depends on the correlation between the sources, as shown in Section 4. For transmission over a noisy channel, the transmission rate needs to be increased according to the channel capacity as $R_{X_n} = p \geq \frac{kH(X_n|X_N)}{C}$.

At the decoder, the information is obtained by applying soft-decoding by means of belief propagation [24] on the Raptor Tanner graph (see Figure 3). To initiate decoding, the decoder is given the following soft-information in the form of log-likelihood ratios (LLRs): In the noiseless transmission case, the LLRs $L[x_n^*(i)]$, which correspond to the parity symbols for the encoded source X_n , are set to a very large positive or negative value (depending on the received symbol).

When transmission is performed over a AWGN channel and

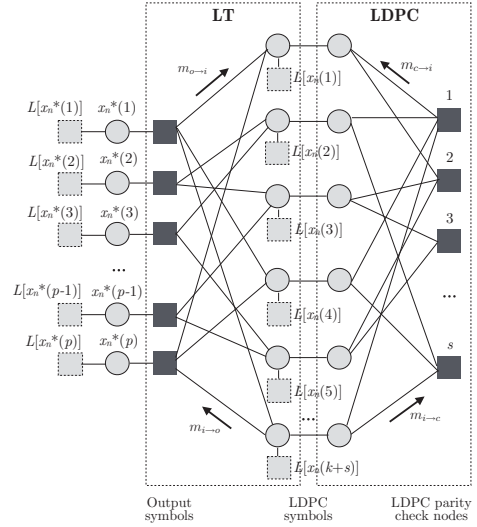


Figure 3: Tanner graph of our non-systematic SW Raptor code.

binary phase-shift keying (BPSK) modulation is used, the LLR of each parity symbol is initialized as [15]

$$L[x_n^*(i)] = \frac{2}{\sigma_n^2} y_n(i), \quad i = 1, 2, \dots, p, \quad (1)$$

where $y_n(i)$ is the value received when $x_n^*(i)$ is sent, and σ_n^2 is the variance of the Gaussian noise. For transmission over a channel experiencing Rayleigh fading (with known CSI) the LLRs are given by [14]

$$L[x_n^*(i)] = \frac{2}{\sigma_n^2} y_n(i) \times r, \quad (2)$$

where r is the fading gain. These channel models are known to characterize the behavior of narrow-band transmission within personal area networks [21]. The LLRs for the information symbols, $x_n(i)$, $i = 1, 2, \dots, k$, are initialized as

$$L[x_n(i)] = \log \frac{\Pr[x_n(i) = 0|x_N]}{\Pr[x_n(i) = 1|x_N]} = \log \frac{\int_{x_n=0} f(x_n|x_N) dx_n}{\int_{x_n=1} f(x_n|x_N) dx_n}, \quad (3)$$

where the numerator of (3) is the integral of the conditional pdf of the correlation model (see Section 4) on the intervals where $x_n(i) = 0$, and the denominator is the integral of the pdf on the intervals where $x_n(i) = 1$.

The LLRs $L[x_n(i)]$, $i = k + 1, \dots, k + s$, which correspond to the parity symbols of the LDPC code, are initialized to zero as these symbols are not known *a priori* at the decoder.

Finally, after Raptor decoding is finished, the soft-information is converted to binary symbols via thresholding, and gray decoding is performed to obtain the decoded information.

4. CORRELATION MODELING

We express the correlation amongst the sensors' temperature measurements through the multivariate Gaussian distribution. Under this model, the joint probability density (pdf) function of the N random variables is

$$f(x_1, x_2, \dots, x_N) = \frac{1}{(2\pi)^{\frac{N}{2}} |\Sigma|^{\frac{1}{2}}} \times \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \Sigma^{-1}(\mathbf{x} - \boldsymbol{\mu})\right), \quad (4)$$

where $\mathbf{X} = \{X_1, X_2, \dots, X_N\}$ is an N -dimensional vector consisting of the correlated random variables, $\boldsymbol{\mu} = \{E[X_1], E[X_2], \dots, E[X_N]\}$ is the vector containing the mean values and Σ is the covariance matrix of size $N \times N$. The statistical dependencies of the measured data from the N nodes within a cluster are incorporated in the covariance matrix. The elements outside the main diagonal can be expressed using the Pearson correlation coefficient

$$\rho_{ij} = \frac{\text{Cov}(X_i, X_j)}{\sqrt{(\text{Var}(X_i)\text{Var}(X_j))}}, \quad (5)$$

where the terms $\text{Var}(X_i)$ and $\text{Var}(X_j)$ represent the variances of the random variables X_i and X_j , respectively. The parameters of the model are estimated based on offline training as explained in Section 5.

In order to derive the LLRs and the encoding rate for each peripheral node, we first derive the univariate distribution, $f(x_N)$, for the marginal statistics of the CH node, that is,

$$f_N(x_N) = \int_{X_1} \dots \int_{X_{N-1}} f(x_1, \dots, x_N) dx_1 \dots dx_{N-1}, \quad (6)$$

and the bivariate distribution.

$$f(x_n, x_N) = \int_{X_{i \neq \{n, N\}}} \dots \int_{X_{j \neq \{n, N\}}} f(x_i, \dots, x_j) \times dx_{i \neq \{n, N\}} \dots dx_{j \neq \{n, N\}}, \quad (7)$$

$\forall n \in \{1, 2, \dots, N - 1\}$. Then, the conditional pdf, required for the calculation of the LLRs in (3), is derived as

$$f(x_n|x_N) = \frac{f(x_n, x_N)}{f_N(x_N)}. \quad (8)$$

To calculate the encoding rate per peripheral sensor we derive the marginal and bivariate probability mass functions (pmfs) for each $n = 1, 2, \dots, N$. To this end, the range of each continuous random variable X_n is divided into intervals of length Δ , specified by the sensor resolution. As the sensor resolution is high (16 bits), we can derive the marginal and

bivariate pmfs by applying the mean-value theorem on the marginal and bivariate pdfs, given in (6) and (7), respectively. Using the marginal and joint pmfs we calculate the entropy $H(X_N)$ and the joint entropy $H(X_n, X_N)$. Then, the conditional entropy for each source X_n given X_N is computed as $H(X_n|X_N) = H(X_n, X_N) - H(X_N)$.

5. EXPERIMENTS

Our experimental evaluations are organized in two categories. Firstly, we evaluate the performance of our non-systematic SW Raptor code design against the state-of-the-art [11] using synthetic data. Secondly, we explore the performance of the proposed DJSCC system using a real WSN deployment.

5.1 Experiments on Synthetic data

To evaluate the SW performance of our Raptor code, we consider a uniform binary source X (where, $\text{Pr}[X = 1] = \text{Pr}[X = 0] = \frac{1}{2}$) and generate data of different lengths, varying from $k = 16$ bits to $k = 5 \times 10^3$ bits. We assume that the correlation between the source and the side information is modeled with a binary symmetric channel (BSC) with crossover probability p_e . Thus, the side information data is given by $Y = X \oplus Z$, where $Z \sim \mathcal{B}(p_e)$ is a Bernoulli correlation noise and \oplus denotes modulo-2 addition. We compare the average² bit-error-rate (BER) performance of our non-systematic SW Raptor code against the systematic SW Raptor code of [11] with respect to the source word length. The crossover probability of the binary symmetric correlation channel was set to $p_e = 0.05$, and the compression ratio was $\frac{1}{H(X|Y)} = 2$. The results, depicted in Fig 4, show that the systematic Raptor code is effective for very long codewords, while our non-systematic code is efficient for short codeword lengths. Hence, our non-systematic SW Raptor code is suitable for body area networks monitoring physical parameters, such as temperature, humidity, etc., where the data rate is low. On the contrary, the systematic SW Raptor code of [11] is more appropriate for body area network applications that involve a high data volume, for example, wireless visual sensors for elderly care monitoring [9, 31], genome sequence compression [33], or wireless capsule endoscopy [7, 8].

5.2 Experiments with WSN Deployment

To evaluate the practical performance of our system, we deployed a proprietary WSN comprising 32 nodes (organized in 8 clusters of 4 nodes) gathering temperature data in an indoor office environment. The sink node was connected to a desktop computer. The hardware for the sensors and the sink node was an Atmel ATmega 1281 microcontroller and the sensors operated with an MCP9700AT Temperature Transducer and a Li-Polymer Battery-3.7V. Transmissions within each cluster occurred via the AT86RF230 transceiver. The payload packet size was set to 60 bytes. The sensors operated at a sampling rate of 4Hz. We aggregated $m = 40$ consecutive measurements to construct a sourceword of size $k = m \times b = 640$ bits, where $b = 16$ bits is the bit-depth of the A/D converter within each sensor. During the training stage, data collected over a three-day operation of the WSN were used to derive the parameters of the correlation

²Results over 200 independent trials are presented.

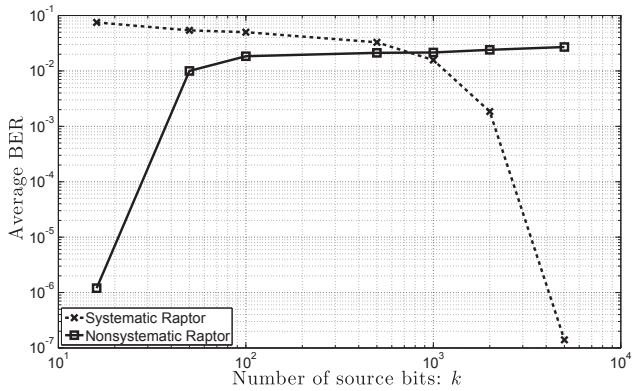


Figure 4: Average BER versus the source length k for our non-systematic SW Raptor against the systematic SW Raptor code of [11].

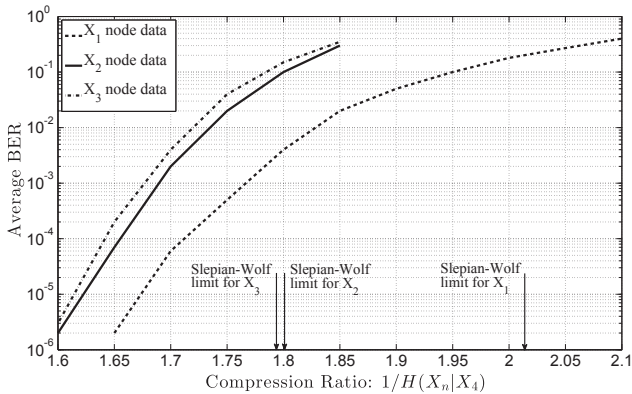


Figure 5: Average BER of the decoded information vs. the compression ratio.

model. To evaluate the compression performance and the error-resilience capability of the proposed system we collected additional data over a thirty-day operation period of the system.

5.2.1 Compression Performance Evaluation

Initially, we assess the compression capacity of the proposed Raptor-based SW code design. In particular, we evaluate the BER of the decoded data from each peripheral sensor in a cluster, $X_n, n = 1, 2, 3$, with respect to the compression ratio $\frac{1}{H(X_n|X_4)}$. Average results over 200 trials³ are presented. The results, together with the theoretical SW limits, are presented in Fig. 5. With respect to the reconstruction quality of the decoded temperature data, BER values below 10^{-6} corresponded to near-lossless recovery. On the other end, values around 10^{-2} lead to maximum root mean squared-error of 128, which corresponded to a temperature error of up to 0.38° , which is below the A/D accuracy of the utilized temperature transducer.

Next, we compare the compression performance of the pro-

³Per trial, a four-day period (out of the full thirty-day period) was selected at random and the corresponding temperature data was compressed.

Table 1: Comparison of source encoding rates (in bits/sourceword) for entropy coding, and the proposed Slepian-Wolf coding scheme (X_4 denotes the CH data that is always entropy encoded).

	X_1	X_2	X_3	X_4
Entropy Coding: R_{X_i}	452	496	512	471
Proposed with MG: R_{X_i}	319	356	358	—
Gain (%)	29.43	28.23	30.08	—

Table 2: Percentile energy consumption reduction versus channel SNR, offered by the proposed DJSCC system in comparison to the baseline system. Transmission over the AWGN and the Rayleigh fading channel is considered.

	AWGN	Rayleigh Fading
SNR (dB)	Energy Gain (%)	Energy Gain (%)
0.5	15.67	15.98
1	15.24	16.51
1.5	14.96	16.14
2	14.94	15.28
2.5	13.38	14.15
3	13.34	15.77
3.5	12.19	16.41
4	13.57	16.07
4.5	12.82	16.34
5	12.31	15.14

posed system against the performance obtained with the baseline system, which performs adaptive arithmetic entropy coding of each sensor's readings. In both cases, lossless encoding is achieved. The encoding rates (in bits per codeword) achieved with the baseline system and the proposed system are reported in Table 1. The results show that the proposed system reduces the required rate for compression by up to 30.08% compared to the baseline system. These gains highlight the importance of properly leveraging the correlation between the data gathered by the sensors in the WSN.

5.2.2 Energy Savings

We now evaluate the energy consumption of a sensor running the proposed versus the baseline system for varying transmission channel conditions. Interference and packet losses cannot be controlled in our practical deployment, as such conditions vary during the operational lifetime of our system due to various external factors. For this reason, we have carried out our evaluation using the AWGN and Rayleigh fading channel models under varying signal-to-noise-ratios (SNR) values. Packet retransmissions are not required by the proposed DJSCC system, as channel impairments are mitigated with the Raptor code present in the proposed design. For our system, we derive the required information rate to achieve a decoding BER close to zero ($\text{BER} < 10^{-6}$) for different channel SNRs. For the baseline system, we calculate the packet retransmission limit that guarantees an equivalent BER.

To conduct our energy measurements, each sensor in our WSN deployment runs executable programs implementing the proposed DJSCC scheme and the baseline system. The

information rates for our system and the packet retransmission limit for the baseline system are preset via the aforementioned channel-model-based measurements. Full packets (80 bytes payload and 12 bytes header) are transmitted by aggregating encoded information from consecutive codewords when required. The Atmel ATmega 1281 microcontroller of each sensor is set to report its battery level during the execution. By gathering the battery level measurements from all sensors at the end of the experiment and converting them to available energy levels, we determine the percentile energy consumption difference between the proposed and the baseline system⁴. Average results over multiple executions and all sensors within a cluster are reported in Table 2. Results for both channel models and different SNR conditions are provided.

We observe that the proposed DJSCC system yields a notable reduction in energy consumption with respect to the baseline system. When transmission faces AWGN, energy consumption savings between 12.19% to 15.67% are reported while, in the case of Rayleigh fading savings between 14.15% to 16.51% are observed. These savings are attributed to the following reasons: First, the proposed DJSCC scheme eliminates packet retransmissions due to the inherent error correcting capability of the code design. On the contrary, retransmissions are used to deal with channel impairments when the baseline system is used. Second, as shown in Section 5.2.1, the proposed system achieves higher compression rates than the baseline system as it exploits the correlation between the readings from different sensors.

6. CONCLUSIONS

A novel DJSCC design for correlated data gathering in local-area or body-area wireless sensor networks has been presented. Our scheme is based on a new non-systematic SW Raptor code design, which, unlike existing schemes (i.e., [11]), achieves good performance at short code lengths. This is particularly important for temperature monitoring applications, where sensors measure low-rate data. Experimentation using a WSN deployment shows that the proposed DJSCC system achieves compression rate savings of up to 30.08% compared to the baseline system that performs adaptive arithmetic entropy encoding of the data. Moreover, our system provides for inherent error resilience against channel impairments without requiring packet retransmissions. As a consequence, the proposed system notably reduces the energy consumption (by up to 16.51%) at a sensor node with respect to the baseline system.

7. ACKNOWLEDGMENTS

The work of N. Deligiannis and Y. Andreopoulos is supported by the EPSRC project EP/K033166/1. The work of E. Zimos is supported by IWT via the ICON LittleSister project.

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⁴This energy consumption difference includes both the computational and transmission parts of the system.

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