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AN ADAPTIVE JOINT SOURCE CODING METHOD FOR ENERGY EFFICIENCY IN WINOC

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Abstract—
A potential solution to the communication difficulties associated with the scalability of multi-core computers is wireless network on chip (WiNoC). However, when using WiNoCs, energy consumption becomes a limitation. To lower the energy consumption of WiNoCs, a number of techniques are suggested, including the use of energy-efficient transceivers and the adaptive disabling of power-hungry modules. In order to lower the energy consumption of WiNoC communication, an integrated source code with adaptive low-density parity check encoding (LDPC) is proposed in this study. SNR estimation is used to make this combined source and channel coding adaptable. In order to decrease communication power consumption, the suggested strategy boosts effective network use and prevents unnecessary decoding processes. Energy consumption is used to assess how well the suggested adaptive joint source coding (LDPC) performs. When compared to current practices, the suggested method can lower power consumption by 4.2%..
Keyword: NOC, Encoding, SNR, LDPC
Acronyms:
WiNoC: Wireless NOC
LDPC: Low density parity check encoding
SNR: Signal to noise ratio
CS: compressive sensing
CR: Compression ratio
OFDM: Orthogonal frequency division multiplexing
BER-Bit error rate
M-QAM- M –Ary quadrature amplitude modulation
FFT: Fast Fourier transform
Low PAN-Low power wireless personal area network.
Log BJCR-Bahl, cocke, jelinek, Raviv
ARQ-Automatic repeat request
DFT –Discrete Fourier transform
PSD – Power spectral density
MLR- Multilinear regression
PSNR –Peak signal to noise ratio
SSIM- Structural similarity index measure

I. Introduction

WiNoC, or wireless network on chip, is crucial for connecting upcoming multi-core architectures. WiNoC expands the traditional network on a chip with wireless connectivity (NoC). By doing this, the network diameter is decreased, and high throughput and low latency data transfers are made possible. The percentage of time spent communicating increases exponentially with an increase in processor count [1]. For applications requiring greater parallelism, communication becomes a bottleneck. An important portion of the total energy budget of multicore systems is consumed by increased communication. Although WiNoC designs enable a greater number of cores by opening up a new design dimension, communication energy is starting to become a problem. A chip's performance and lifespan can be negatively impacted by increased energy consumption, which can also produce temperature hotspots [2, 3]. As a result, it has become a study topic of interest to lower the communication energy in WiNoC. Reduce the number of transmissions to reduce the amount of energy required for communication.This study employs a combination source coding (compression) and channel coding (bit interleaving) technique to reduce the number of transmissions.Under a delay restriction on a time-varying channel, joint source-channel encoding attempts to achieve joint optimality of source coding and channel coding. A network communication system performs better because of joint channel-network coding, which offers dependable communication [4]. This work combines LDPC channel coding with compressive sensing-based source coding to produce a joint source code for LDPC. Based on the predicted SNR, compressive sensing (CS) and LDPC are both modified. In order to reduce energy usage, the LDPC is modified to adjust the compression ratio (CR) and shunt unneeded decoding processes. In the event of decreasing SNR, the compression ratio is maintained at a lower level. If the SNR is larger, the compression ratio rises at the expense of the source data's accuracy. The compression ratio is managed by a fuzzy logic algorithm that takes application reliability feedback and the estimated SNR as inputs. Based on the predicted SNR from the regression fit and the reliability level, the parity check operation of the LDPC is adaptively shunted off. The novel contributions of this book are listed below. Combined source and channel coding is adaptive to SNR estimation with the goal of maximising network utilisation and minimising energy consumption.

(i)LDPC channel coding and fuzzy reasoning algorithm integration for compressive sensing with fine-tuned compression ratio

(ii)An adaptive shunt off decoding technique with low overhead that is based on regression fit

The remainder of the essay is structured as follows. The survey of current WiNoC data encoding techniques is described in Section II. The proposed combined source and channel coding system is described in Section III. The findings of the suggested solution are presented in Section IV, along with a comparison to earlier efforts. The final thoughts and the range of additional investigation are presented in Section V.

II. Related Work

In order to decrease the power dissipation at NoC links, Jafarzadeh et al. [5] presented a number of data encoding techniques. The plans center on reducing switching and coupling activities, which account for the majority of power loss. The solution is only applicable to wired NoC and only certain work patterns. Additionally, the strategy does not adapt to the system's present residual energy. Two data encoding methods were presented by Chennakesavulu et al. [6] with the intention of reducing power consumption and enhancing dependability. The two data encoding methods that are suggested in this work are based on reducing coupling and self-switching activities at the link interconnect. The method is only applicable to exchanges of lower bit rates and cannot be expanded to larger bit rates. Zero Aware Configurable Data Encoding by Skipping Transfer is the name of the data encoding method Jha et al [7] suggested. This plan trades off application precision for energy conservation. By taking advantage of the similarities between recent data transfers across channels, the amount of 1s broadcast in the channel is decreased. The output accuracy loss is roughly 10% even though the solution can provide 37% switching energy. A brand-new turbo decoder method was put forth by Dujaily et al. [8] to do away with the Log BCJR algorithm's reliance on data. Throughput was significantly improved by the suggested approach by up to 213%. Only nearby nodes are permitted to communicate under the proposed solution, which restricts connected topology. Network coding and forward error correction were used by Biczók et al. [9] to lessen the detrimental effects of contention at the network layer. Using the network redundancy network that network coding introduces into the encoded packets, the contenting packets can be bound with XOR. This increases the likelihood that both packets can be decoded without the need for retransmission. Retransmission energy loss is also prevented by preserving the retransmissions. However, this technique performs worse in the presence of reduced SNR. For on-chip wireless interconnects, Gade et al [10] used an OFDM transceiver operating at millimeter wave frequencies. For great spectrum efficiency and adequate BER, M-QAM data encoding was utilized as the solution. The FFT module is reused to reduce the area. Although the technique has higher interference at shorter distances than wires, energy savings are better for longer distances. By integrating a parallel decoder, Condo et al. [11] merged the data processing and message passing phases of LDPC. Higher throughput can be achieved using parallelism. But the predicted SNR is not taken into account for any parity checking processes. This results in a higher energy consumption using this method. Seven coding schemes and their variations were examined by Zhan et al. [12] for their applicability in high performance wireless networks. Bit-error rate, packet error rate, and throughput were compared between the approaches. The study found that LDPC's built-in parallel decoding was preferable to turbo. LDPC code has a higher throughput because of parallel decoding. The paper suggests using LDPC in combination with other codes, such as RS, to get around the error floor and mitigate latency issues. On top of this suggestion, our work combines CS with LDPC. Signature coding was employed by Dehyadegari et al. [13] to lower the energy usage on-chip. Combining signature encoding and transition signaling lowers the switching activity on the links. By using signature encoding of the body and tail flits while omitting the header flit, the amount of 1s is decreased. As a result, there is less switching activity and hence less energy usage. However, the strategy is only effective for lower bit transfers. Flexible turbo coder was offered by Lapotre et al. [14] for increased throughput and energy efficiency. The turbo programmer thought about dynamic reconfiguration, which enables run-time configuration management at the frame-by-frame level. To lower the energy usage in 6LoWPAN networks, Amanowicz et al. [15] presented an inter session network coding scheme. The packets are buffered, then using a bitwise XOR operation, unicast packets from two sessions are converted to broadcast packets. At the receiver end, the packets are subsequently decoded. The energy usage is decreased by encoding two unicast packets and sending them as one packet. However, the method causes latency because of buffering. For serial links, Velayudham et al. [16] devised a low power encoding technique. By eliminating switching transitions, this strategy reduces energy consumption. Three phases make up the proposed encoding. The first stage involves converting binary data to grayscale. To reduce self-transition, bits are shifted in the second step. The third stage involves double binary to grey coding. In order to minimize switching-related power consumption, the encoding word with the lowest transition count is chosen at each stage. Shao et al. [17] examined the throughput, flexibility, error-correcting ability, space efficiency, and energy efficiency of turbo, LDPC, and polar decoders. According to the study, LDPC decoders outperformed turbo and polar decoders for the majority of coding rates in terms of both area and energy efficiency. For longer blocks, the error-correcting capacity was the same across all decoders, however polar coding outperformed them for shorter blocks. Better throughput and flexibility were provided by LDPC. Because of LDPC's improved performance, we decided to combine it with CS in this article. A low power LDPC decoder was suggested by Park et al [18]. The decoder bases its decision-making on the estimated SNR. By avoiding procedures that are unnecessary, energy can be saved. For higher SNR, the energy savings are insignificant, and the method is not adaptable to the system's present residual energy. Using SNR feedback, Jung et al. [19] modified the scaling factor (SF) of the NMS LDPC decoding algorithm. The approach made decoding less complex while maintaining BER. However, the algorithm could not handle larger data rates. An energy-efficient LDPC using an adaptable word width data route was presented by Mohsenin et al [20]. The decoder has two modes of operation: standard mode and low power mode. The received SNR and BER requirements are taken into account when switching modes. Both the full word width computation and the reduced word width computation are performed in normal and low power modes, respectively. In order to decrease the decoding delay and power consumption, Pourjabar et al. [21] devised a variable rate LDPC decoder. Lower data rate is produced by adding additional parity bits to an existing parity check matrix. However, this is only used in ARQ when the decoder fails the first time. In this method, as SNR is decreased, the coding rate also decreases.

Adaptive joint source coding LDPC

The suggested remedy uses two ideas—LDPC-based error correction coding and compressive sensing-based source coding—and it is compatible with the WiNoC paradigm.

With the use of compressed sensing [22], the original signal can be recreated using fewer observations. We can go above the Shannon limit and represent the compressed signal below Nyquist rate by taking advantage of the signals' sparsity. By employing non-adaptive linear projections, the encoding is quick and effectively preserves the signal's structure. Only the most crucial aspects of the signal are acquired using compressive sampling. Various optimization approaches are used to reconstruct the original signal from the projections. In Figures 1 and 2, the basic building elements of compressive sensing are shown. By sampling below the Nyquist rate, compressive sensing can produce greater data rates, as seen in Figure 1.

Working with a sparse representation of the signal has made this possible. The ratio of the signal sparsity to the compression efficiency.

Let x be the original signal and its sparse representation in some orthogonal basis is given as $\varphi = \{\varphi 1, \varphi 2, .. \varphi N\}$ where the length of the signal is

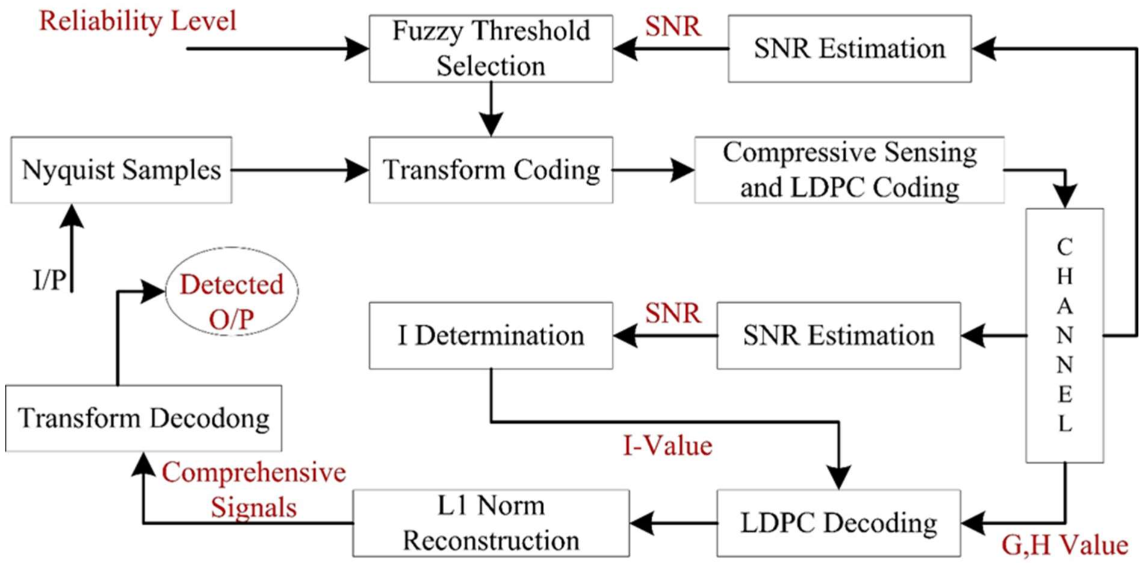

Figure 1: Proposed Adaptive Joint source LDPC Encoding

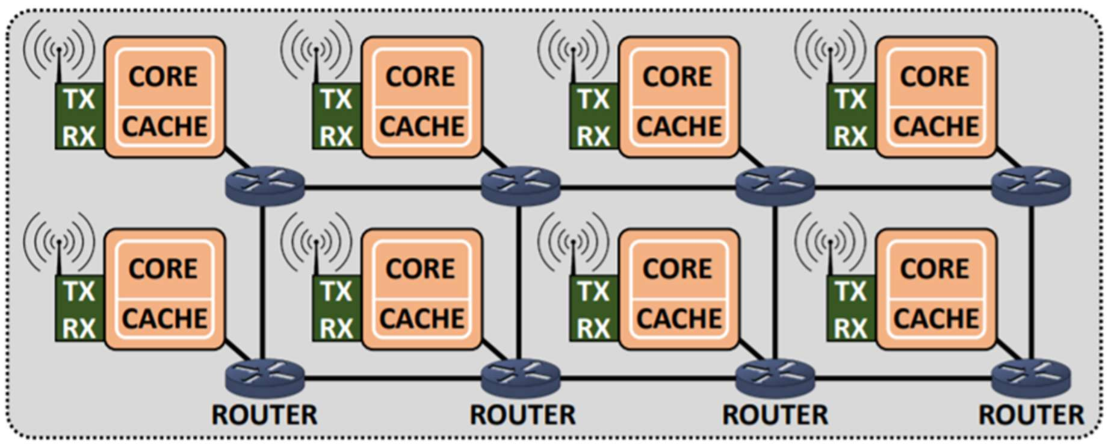

Figure 1 Wireless NOC Configuration

N. The signal x can be represented in term of K linear combination of basis functions ($K \ll N$) as

$$x = \sum_{i=1}^{K} \emptyset_{ni}\, \varphi_{ni}$$

Where $\varphi ni \in \varphi$. Let $\emptyset = [\emptyset_1, \emptyset_2, \ldots . \emptyset_N]^T$ be the vector of coefficients of the signal x in φ. The random measurement of the signal x is given as

$y = \phi\emptyset$

$\phi: M \times N$

$K < M \ll N$

y is the measurement vector of the signal x, and is the uniform random measurement matrix. In order to successfully reconstruct the signal, M = cK(c<1) measurements must be taken, where denotes the coefficients for the signal x. When all of the entries in are drawn from a Gaussian distribution, the reconstruction can be performed with more precision. Transform coding is used to transform signals that are not sparse in their original form into sparse representations [23]. To acquire coefficients in transform coding, the whole signal is captured in Nyquist rate and subjected to the Discrete Fourier Transform (DFT). Coefficients with values below the fixed threshold are made to be zero. In the modified domain, the signal is made sparse in this manner. The observation vector of length M is then obtained by multiplying the sparse representation by the measurement matrix. The interest signal has been compressed with the use of sparse representation. Measurement matrix and measurement vector y are two variables that affect how well the reconstruction is performed. It is possible to retrieve all K coefficients from the M measurement of y when the matrix exhibits near orthonormal restricted isometric characteristic. L1 norm minimization and convex optimization are the two most popular optimization strategies for reconstructing the sparse signal. The goal of l1 norm minimization is to identify the vectors with the lowest l1 norm.

$$min||x||n \ subject \ to \ \phi x = y$$

The threshold chosen for transform coding determines the sparsity. This paper suggests an adaptive threshold based on the expected SNR of the channel and the desired reliability of the application as an alternative to hard thresholding. The threshold (T) is calculated as $T = Tb *$ max (Xi)

Where X_i is DFT transformation $_N$ $_1 x_i(k)$ given as

$$X_i(k) = DFT\big(x_i(n)\big) = \sum_{n=0}^{-} x_i(n)e^{-j\frac{2\pi}{N}kn}$$

Based on the predicted SNR and desired dependability for the application, a threshold base (Tb) is determined. Based on the power spectrum density (PSD) of the received signal, the SNR is estimated. The PSD is used to calculate the posteriori and priori SNR as

$$\boldsymbol{SNR_{\widetilde{post}(s,t)}} = \frac{|\boldsymbol{X(s,t)}|^2}{\tilde{\boldsymbol{\gamma}}_{\boldsymbol{n}}\boldsymbol{(s,t)}}$$

$$SNR_{\widetilde{pri}(s},t) = \beta\frac{|\bar{S}(s-1,t)|^2}{\tilde{\gamma}_n(s,t)} + (1-\beta)P[\overline{SNR}_{post}(s,t)-1]$$

The rectification of a half wave is called P. $\bar{S}(s-1,t)$ represents the estimated spectrum for the preceding frame. , which ranges in value from 0 to 1, is the behavior control parameter.
In the range of 0 to 1, the application gives the appropriate reliability level. When an application wants the highest level of reliability, the reliability level value is 1, and when there is less demand for reliability, it is 0. The application-desired dependability level (rL) and estimated SNR (SNRpri) are used to model the threshold base (Tb).

$$F(T_b) = \mu_1 * Q(SNR_{pri}) + \mu_2 * Q(r_L)$$

Where Q(x) is the fuzzification kernel for input x. The de-fuzzification is done using center of gravity method as

$$T_b = \frac{\int \mu_{\bar{D}r}(x).xdx}{\int \mu_{\bar{D}r}(x).dx}$$

Where x = {SNR_{pri}, , r_L }.

Using the transformation algorithm shown in Figures 3 and 4, the variables SNRpri and rL are normalized and transformed to fuzzy variables. Figure 5 provides the transformation function for threshold base (Tb).

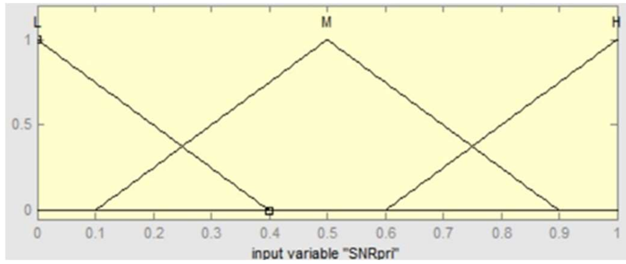

Figure 3 SNRpri transform function

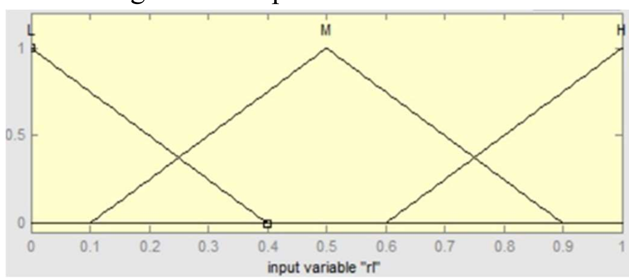

Figure 4 rl transform function

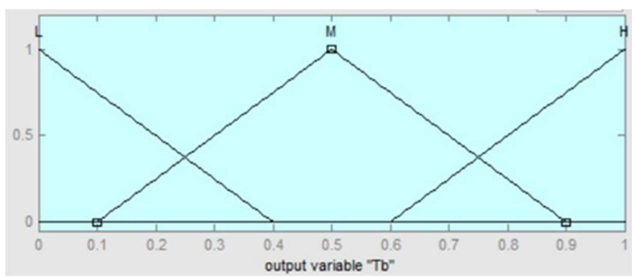

Figure 5 Tb Transform function

The rule base for mapping the input variables SNRpri and rL to threshold base Tb is given in Table 1. Table 1 Rule base

$\mathbf{SNR_{pri}}$	$\mathbf{r_L}$	$\boldsymbol{T_b}$
L	L	H
L	M	H
L	H	M
M	L	M
M	M	M
M	H	M
H	L	L
H	M	L

H	H	M

$$T\big(X_i(k)\big) = \begin{cases} 0 & ,\forall\ |\mathrm{Xn_i} < T \\ X_i(k)\ \omega(|\mathrm{Xn_i(k)}|), & |\mathrm{Xn_i}| \geq T \end{cases}$$

The threshold is applied as below on $Xi(k)$ to get the spare representation

The compressed signal is then obtained by multiplying the spare representation by the measurement matrix. The adaptive LDPC coding process moves on to the next stage with this compressed signal.

A linear block code for error correction is called LDPC [24]. It made use of the H-matrix parity check matrix. It is more favored than turbo coding because of its little floor error and efficient parallelization. The two incredibly sparse matrices G and H define the coding. The message that will be conveyed is encoded using the G matrix. The message is decoded at the receiver using a H matrix. Compared to encoding, LDPC decoding is a computationally demanding process. Iterative decoding is used, and the bi-partite graph representation of the H-matrix is the source of this iterative computation (Figure 6). Bit (variable) nodes and check nodes are the two different sorts of nodes in this graph. The row and column weights of the H-Matrix, where the weight is the number of 1-entries in the row/column, determine the connections between the two nodes in the bipartite graph. The number of bit nodes is represented by columns, and the number of check nodes is represented by rows. Additionally, the number of rows defines how many check bits are included in the encoded message, and the number of columns dictates how many bits are included in the decoded message. An approach of code rate adaptive allocation strategy from image transmission and enhanced image reconstruction using k++ means algorithm is presented in Paper [25]. Similar LDPC codes that aim to reduce implementation complexity and hardware resource utilization are also proposed in paper [26].

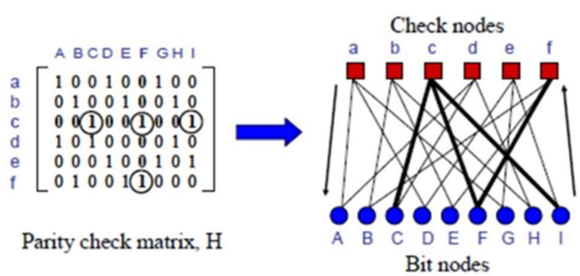

Figure 6 H Matrix to bipartite graph

The bit node and the check node, two processing units, carry out iterations of message passing [2]. To decode a word, each type of node interacts with a number of nodes that are all of the opposite type. Based on the likely values of the other bits that are involved in the same check as y, the goal is to calculate the likelihood that an encoded bit y will have a logic state of either 0 or 1. The probability of bit y is similarly used as an input in all check operations involving bits y to the function that calculates the probabilities of all other bits. The likelihood that bit y will eventually converge to either zero or one is the consequence of this iterative operation. The bipartite network has a rather large number of edges because the H matrix, albeit sparse, is fairly massive in order to decode large blocks of data [2]. Additionally, each node's computation needs information from other nodes for a specific computation iteration. Decoding is computationally and energy expensive since iterative algorithms are used.

This study suggests an adaptive LDPC to limit the amount of decoding iterations. This results in less processing and energy use. If the parity check equations are fulfilled early, the number of iterations can be decreased. This study proposes to adapt LDPC based on estimated SNR value, drawing from the conclusions of [8], that higher number of iterations are needed for lower SNR value and lower number of iterations are needed for higher SNR value. In addition to [8], this study incorporates application reliability to limit the amount of LDPC repeats.

The processes of check node operation, variable node operation, and parity check are repeated repeatedly in conventional LDPC. Based on the predicted SNR value and application reliability level, this work tries to delay performing parity checks for a predetermined amount of iterations. The maximum quantity of information that can move across a channel without error is indicated by the Shannon information transmission capacity C, which is expressed as $C = \mathrm{w}\, Log_2 2 \left(\frac{S}{N} + 1\right)$

The smallest number of iterations required for successful LDPC decoding is discovered after doing a dry run for various SNR values and application dependability levels. The next mapping table is created in the same manner as

Table 2. Table 2 I mapping table

SNR_{pri}	r_L	I
Xx	Xx	Xx

From this mapping table, a multi linear regression(MLR) is fitted with goal of minimizing the $l2 - norm$ of the coefficient vector (w)

$$\min\left(\frac{1}{2}||w||^2\right)$$

subject to the constraint of

$$|I_i - w_{1i}SNR_{pri} - w_{2i}r_L| \leq \epsilon$$

where the fitting error tolerance is ϵ.

After the regression model has been fitted, the reliability level and SNR estimate are determined for any new incoming data at the receiver. To obtain the I value, MLR regression fit is provided with both of these inputs. When using the traditional LDPC coding, the parity operations are skipped up until I value times.

The modified LDPC decoding algorithm is given below

Algorithm: Modified LDPC Decoding

1.set iteration number i=0, and $F_n(LLR)$ for bit nodes (n=1,2,…N) and for each (m,n) if $H_{mn} = 1$ set $Z_{mn} = F_n(10)$

2. *while i<=i_{max}*
3. *for all (the check node) do*

Where each set (m,n) if $H_{mn} = 1$

$L_{mn} =$

$(\prod_{n' \in N(M) \backslash n} sign(Z_{mn'})).\, min_{n' \in N(M) \backslash n} |Z_{mn'}| \alpha$

end for

5. *for all (the bit node) do* *Where each set (m,n) if* $H_{mn} = 1$ *Update*

$$z_{mn} = F_n + \sum_{m' \in M(n) \backslash m} L_{m'n} \qquad z_n = F_n + \sum_{m \in M(n)} L_{mn}$$

end for

6. ***if i > I***
7. ***for all*** $\hat{c}_n$ ***for (n=1,2,..N) compute all tentative do***

$$\hat{c}_n = [\hat{c}_n], \begin{cases} \hat{c}_n = 1 \; if \; z_n > 0 \\ \hat{c}_n = 0, if \; z_n < 0 \end{cases}$$

end for

8. ***for all*** $\hat{c}^{n}$ $\mathbf{0}\; \boldsymbol{return}$ ***for (n=1,2,…N) parity check do***

$$\boldsymbol{H}.[\hat{c}_1, \hat{c}_2, \ldots \hat{c}_n]^T = \begin{cases} \boldsymbol{success} \\ \boldsymbol{1, i++continue} \end{cases}$$

endfor elseif *i++ continue; endif end while*

The standard LDPC decoding method skips steps 7 and 8 based on the anticipated SNR and application dependability level. Figure 1 depicts the architecture of the suggested adaptive joint source LDPC coding.

Transform coding is used to provide spare representation once the source signal is sampled at the Nyquist rate. Fuzzy logic is used to determine the threshold for transform coding based on the estimated channel SNR and required reliability level for the application. Following that, the spare representation is compressed sensed and given to the LDPC encoder. The signal that results is sent over the channel. SNR is calculated at the receiver, and LDPC decoding is optimized to forego some parity check operations. The compressive sensing signal is recreated using the LDPC decoded signal and l1 norm reconstruction. The original signal is then obtained by passing this signal through transform decoding.

IV. Results

For an 8-core wireless network on chip design shown in Figure 2, the performance of the suggested method is simulated in Matlab. The cores routing is done using wormhole switching. Smaller pieces of the data packets are split up, flown between nodes, and routed. Table 3 lists the simulation setting parameters.

Table 3 Simulation configuration

Parameter	Value
Number of WRs	8
Switching technique	Wormhole

Packet injection rate	0.001
Traffic distribution	uniform, complement Bit-
radio access control mechanism	token-based
wireless data rate, Gbps	16
packet length, flit	12
flit size, bit	64
router input buffer depth, flit	4
Wireless receiver input buffer depth, flit	4
WR antenna buffer size, flit	64
clock_Period_ps	1000
reset_time cycles	1000
simulation_time cycles	10,000

Different image sizes are tested on the encoder components. Measurements of the performance include BER, PSNR (dB), delay (ms), and power consumption (mW). The delay is determined as

$$d = \frac{\sum_{i=1}^{N_{packet}} (T_{del_i} - T_{gen_i})}{N_{packet}}$$

Where T_{del_i} is the cycle time when i[th] packet is delivered and T_{gen_i} is the cycle time when i[th] packet is sent from source.

The power consumption is measured as average of sum of total energy consumed(E) in all the nodes and its transceivers.

$$E = \mathrm{E}^{proc}(\mathrm{t}) + \mathrm{E}^{T}(\mathrm{t}) + \mathrm{E}^{R}(\mathrm{t})$$

$\mathrm{E}^{proc}(\mathrm{t})$ is the energy spent at node over time t $\mathrm{E}^{Tx}(\mathrm{t})$is the energy spent in transmission of flit over time t $\mathrm{E}^{Rx}(\mathrm{t})$ is the energy spent in reception of flit over time t

$$\mathrm{E}^{proc}(\mathrm{t}) = \mathrm{t} * f_c * P_s * \Phi t_s$$

Where f_c is the core's operating frequency

P_s is the processing power of core

$\Phi t_s$is the duration of operation of core

Transmission energy consumption is given as

$$\mathrm{E}^{T}(\mathrm{t}) = \mathrm{AvgNF}_{T} * P_{T} * \Phi t_{T}$$

$$\mathrm{AvgNF}_T = \mathrm{NF}_T * \frac{1-\left((1-(1-\eta)^2\right)^{R+1}}{1-(1-(1-\eta)^2)}$$

$$\mathrm{NF}_{Tx} = \mathrm{t} * f_{Tx} \;\; \& t \;\; \leq \; \mathrm{LT}$$

Where
ANF_{Tx} is the average number of transmitted flit
P_T
Φt_T is the duration of transmission
NF_{Tx} is the total number of flit transmitted
η is the error probability
R is the number of retransmission

Reception energy is given as

$$\mathrm{E}^R(\mathrm{t}) = \mathrm{AvgNF}_R * P_R * \Phi t_R$$

$$\mathrm{AvgNF}_R = \mathrm{NF}_T * (1-\eta) * \\ * \frac{1-((1-(1-\eta)^2)^{R+1}}{1-(1-(1-\eta)^2)}$$

Where
AvgNF_R is the average number of received flit
P_R is the received power
Φt_{Rx} is the duration of reception NF_{Tx} is the total number of flit transmitted
η is the error probability
R is the number of retransmission

When the SNR is changed from -5 to 10 dB, the performance is evaluated. Performance is contrasted with proposed signature coding technique in [13] and CVR LDPC in [21]. The BER results for varied SNR are provided in Figure 7.

Figure 7.

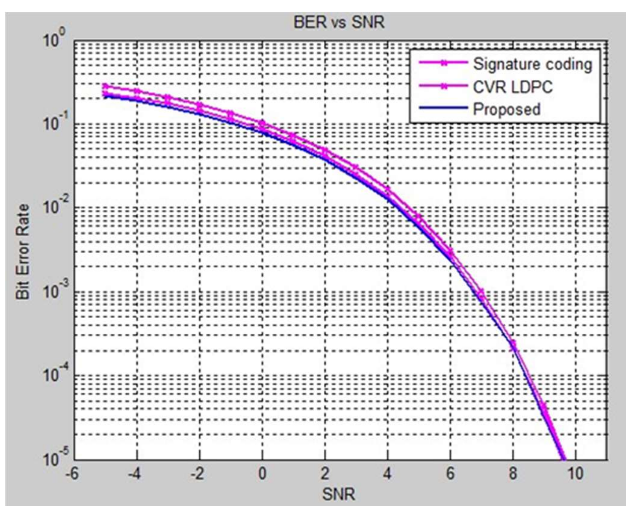

Figure 7 BER vs. SNR

The suggested solution has lower BER overall SNR even if there is no appreciable difference in BER. Although the suggested approach decreased the initial parity tests, the decoding accuracy was unaffected. Additionally, in the proposed method, the threshold value is higher for lower SNR, but it is lower for higher SNR, which causes the BER to decrease as SNR rises. However, as compared to earlier works, the BER for the proposed solution is still higher. PSNR is measured for images of different resolutions and the result is given in Table 4.

Table 4 Comparison of PSNR

Resolution	Proposed	Signature coding	CVR LDPC
128*128	48.15	45.24	46.20
256*256	53.25	49.23	50.55
512*512	57.81	52.29	54.85

With an increase in image resolution, the PSNR rises. PSNR, however, is higher in the suggested solution than in the existing works. The average PSNR in the suggested solution is 4.78 percentage points higher than CVRLDPC and 7.82 percentage points higher than signature coding. In comparison to signature coding and CVRLDPC, the PSNR is higher since the BER is low and the average mean square error between the original and received image is very small. The delay (ms) is measured for different size images and the result is given in Table 5.

Table 5 Comparison of Delay

Resolution	Proposed	Signature coding	CVR LDPC
128*128	69.9	61	66
256*256	110.9	99	105
512*512	155.9	126	136

The proposed approach has a minor increase in latency. In comparison to signature coding and CVR LDPC, the average delay for the suggested approach is 1.4 and 0.7 percent higher, respectively. Due to the suggested solution's l1 norm-based compression signal reconstruction, the delay is marginally larger.

The results of measuring the overall power usage for transmission of 8 images at various resolutions are shown in Table 6.

Table 6: Comparison of Energy consumption

Solution	Power Consumption (mW)	Encoder side consumption (mW)	Decoder side consumption (mW)
Proposed	157	51	105
Signature coding	164.21	75.1	89.21
CVR LDPC	162.42	54.12	108.27

In comparison to signature coding and CVR LDPC, the proposed solution's power consumption is at least 4.2 and 4.91 percent lower, respectively. Due to a decrease in the number of parity check operations, the power consumption in the proposed approach has decreased. The results of measuring the energy consumption for various dependability levels are shown in Table 7. The proposed approach lowered energy consumption by 70 mW for a 0.5 dependability level reduction. For every 0.1 increase in reliability, the energy consumption increased by 14.2 mW on average.

Table 7 Energy consumption vs Reliability level

Reliability level	**Energy consumption(mW)**
0.5	129
0.6	145
0.7	157
0.8	167
0.9	179
1	199

Table 8 displays the results of measuring the PSNR at various image resolutions and reliability levels. The PSNR decreases along with a decline in reliability level. In cases of 512*512 resolution, the decrease is often 2%; in cases of 256*256 resolution, it is typically 3%. The decrease in 128*128 resolutions is typically 5%. Therefore, for better quality photos in the suggested approach, a lower dependability level might be used. The results of measuring the SSIM for various dependability levels and image resolutions are shown in Table 9. The SSIM declines with declining dependability level, and the decline is fairly uniform for photos at all three different resolutions. For eight photos, the performance of the suggested method is evaluated for various levels of reliability in terms of SSIM and PSNR (Figure 8). Figure 9 provides the SSIM for numerous photos at varying reliability levels. The SSIM declines as the dependability level declines, and this decline is constant across all images. However, the decrease is not greater than the typical 18% dependability decline from 1 to 0.5. For all of the photos, PSNR (Figure 10) decreases as dependability level increases. When the reliability level drops from 1 to 0.5, the decline nearly disappears, dropping by an average of 6dB.

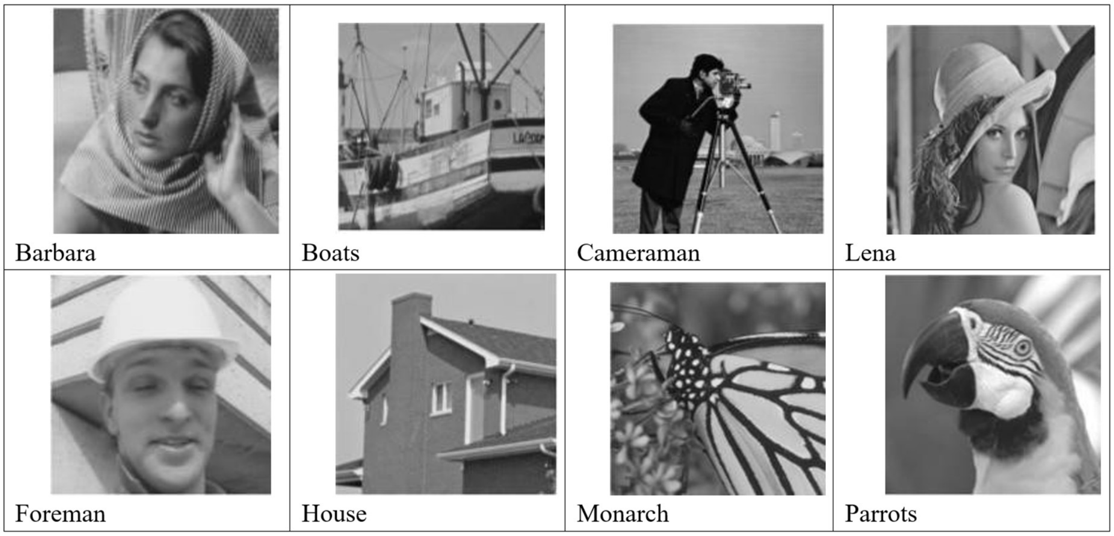

Figure 8 Images for testing

Table 10 Comparison to existing works

Features	Proposed	Signature coding	Variable rate LDPC
Data rate	Compressive sensing results in a higher data rate.	lower data rate because switching activity is lower	Reduced data rate due to lesser SNR
Data quality	Higher sparsity results in greater data quality.	lowered data quality as a result of switching mistakes	Good data rate
Energy consumption	Due to the shunting of iterations in the decoder side, energy consumption is decreased.	As data volume increases, energy use also rises.	The more iterations the decoder runs through; the more energy it uses.

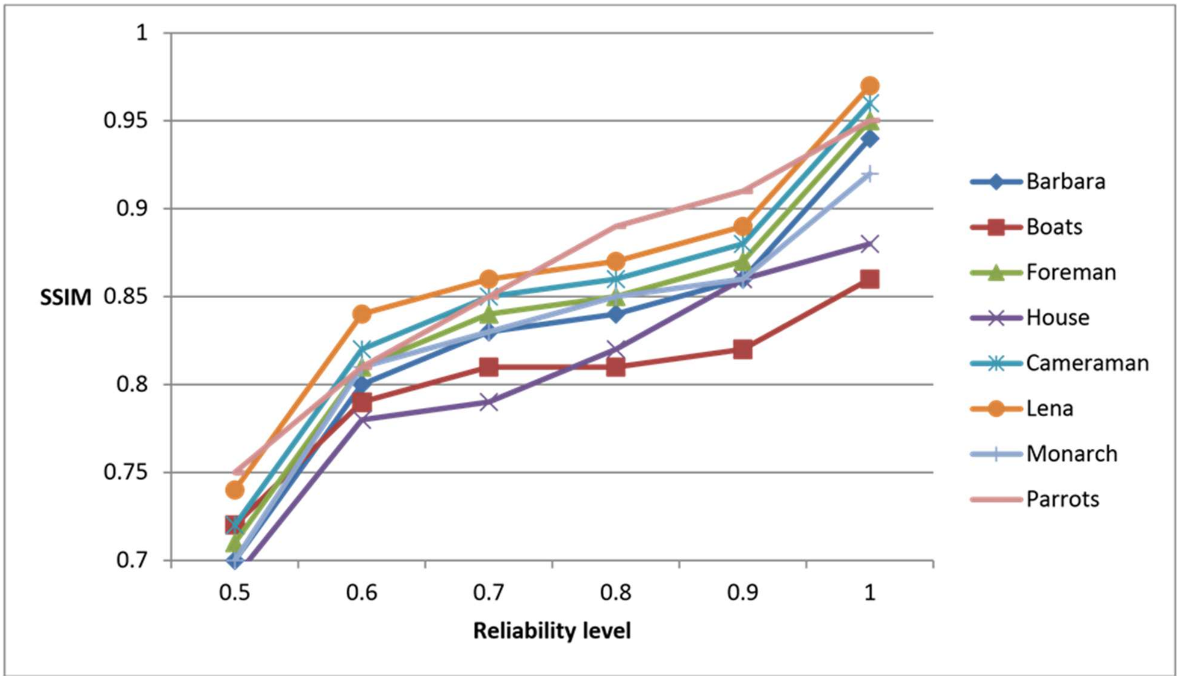

Figure 9 SSIM for different images

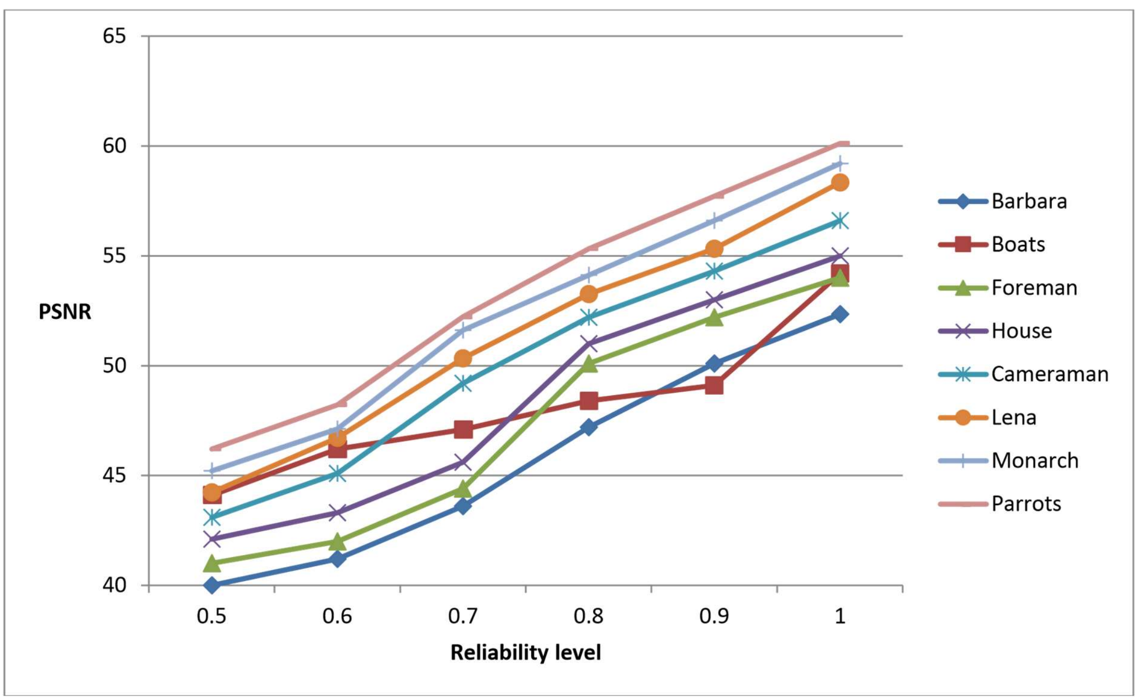

Figure 10 PNSR

The area overhead for various cores were measured in proposed solution and the results are given in Figure 11.

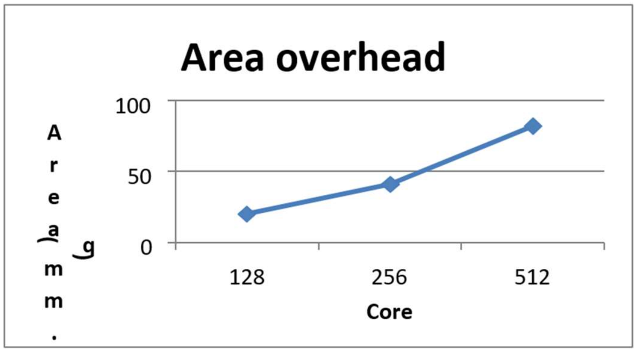

Figure 11 Area overhead

The area increased by almost 100% for doubling the cores.

Discussion:

By minimizing switching activity, the Dehyadegari et al. [13] suggested signature coding system lowered energy consumption. The switching activity was decreased through the application of signature coding. Data rate was the key component of the energy-saving method. Due to signature coding, several bits were anticipated at the decoder end, which had an impact on the image's quality in terms of PSNR and SSIM. Parity check extension was employed in Pourjabar et al variable's rate LDPC [21] to decrease decoding time and energy usage. However, the suggested remedy used a different approach of compressive sensing to cut down on transmission volume and minimal energy overhead LDPC decoding. The data rate is not decreased by this. Additionally, compressive sensing is effective for the DCT-based sparsity that is added to the images in the suggested approach. With a decrease in SNR, the performance of variable rate code in terms of code rate decreased. However, the compression ratio is raised in the suggested solution without altering the coding rate. SNR-based adaptive iteration shunting is the proposed solution. This decreased the number of computations required for decoding in the suggested approach, but in the variable rate code LDPC scheme, decoding required all available iterations, making it impossible to reduce energy usage. Table [10] lists the benefits of the suggested method in comparison to Signature coding and Variable rate LDPC.

V. Conclusion

This paper suggests an adaptive joint source LDPC encoding. In this work, two separate adjustments are made to lower the overall energy use. The data is compressed by adjusting the threshold for transform coding in compressive sensing. Energy consumption and delay are decreased via LDPC coding that limits the number of parity checks. Based on the calculated SNR and the necessary application reliability, adaptation is carried out. Without requiring any new hardware, the suggested method can lower power usage by at least 4.2 percent when compared to the current system. The suggested work's future directions include bringing the algorithm's adaptive character by employing a predictive modelling scheme with a machine learning-based algorithm that is comparable to the method used here in terms of fuzzy logic for threshold setting. With the selected topology and network, a machine learning system using supervised learning techniques can reduce power usage.

Conflict of interest: On behalf of all authors, the corresponding author states that there is no conflict of interest.

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