A Low-Resources Hardware-based Audio Data Compression Scheme for Wireless Sensors Networks

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ABSTRACT
Over the last two decades, the Wireless Multimedia Sensors Networks (WMSN) technology have become increasingly popular by both actual industrial users and research community, they are used for recording speech and then sending it to a base station. However, their limited amount of resources (power, low capacity of radio waves, bandwidth, memory, processing, storage, etc.) makes it important to save resources in order to extend the life of the sensor as long as possible. This paper aims to propose and evaluate an adaptive lifting wavelet encoding hardware solution for audio data compression in WMSN, with require low memory, low computation and low energy consumption. The simulation results show that the proposed approach is efficient and satisfactory compared to the Discrete Cosine Transform (DCT) approach, since it allows 32.6% storage savings and 47.84% energy savings were achieved.

General Terms
Wireless Sensor Network, Applications of Computer Science in Modeling, Visualization and Multimedia, Data compression, Wavelet Representations, Speech and Signal Processing

Keywords
Audio signal, Compression, Energy-efficiency, Wavelet, Wireless sensors networks

1. INTRODUCTION
The latest audio formats are designed to achieve higher performance than in the early days of the digital audio industry. Today, digital-to-analog converters that provide exceptional performance in terms of power supply and isolation circuits, and preserve the integrity of the digital audio signal during each stage of transport can be found. However, Wireless Sensors Networks (WSN) are composed of infrastructure-less (storage, CPU, bandwidth, power, etc) electronic devices designed to measure the physical parameters from physical environment in which they are deployed, and then the sensing data is processed before being transmitted to a remote location information system [1]. WSN processing digital audio data are becoming an important part of military, industrial and medical experiences.

However, given that wireless sensors nodes, over the recent years multimedia data (images, videos, audio streams along with scalar data) compression has been a topic of increased interest. Compression has become a fundamental tool in WSN, due to the limited sensor resources [2]. The applications of WSNs span a wide range including environmental monitoring, multimedia data collection, security monitoring, surveillance, industrial applications, classification, detection, target/object tracking and health care, just to mention a few [3], [4], [5]. Moreover, for domain specific and task oriented applications, nowadays WSN technology has been identified as one of the key components in designing future Internet of Things (IoT) platforms [6], [7]. Most of the sensors are power constrained since they are equipped with small sized batteries, which are difficult or impossible to be replaced especially in hostile or inaccessible environments. However, the sensor usually generates huge amount of redundancy data that consumes sensor resources during storage and communication operations. Hence, the most challenging problem in WSN is resources efficient transmission of the data collected. When considering audio surveillance systems, it is worth noting that they represent an atypical WSN application class since they impose contrasting requirements. At the same time, the available communication bandwidth (limited) needs to be used efficiently while exchanging information.

The proposed approach permits to quickly and easily compress sound waves and digital audio in WSN, given that speech is more structured signal with a band-limited around 4kHz. Unlike current traditional compression audio coding schemes such as MPEG, MP3, OGG, WMA, or AC-3 standards which not only require a lot of resources (high computational overhead), but also permanently remove quality to save space (lossy compression). Due to which it is not feasible to implement them in energy-constrained WSN. Thus, WSN is inherently resources constrained and requires an efficient data compression technique. Thus, desirable or lossless data compression is very important in designing WSN for task oriented as well as IoT based information systems.

The continuation of this paper focuses on audio signal compression in WSN, the related work on audio compression is presented in Section 2, the proposed approach is described in Section 3, the implementations and interpretations of the results are presented in Section 4, from which a conclusion and perspectives are drawn in Section 5.

2. RELATED WORK

The early work on signal compression was laid out by Claude Shannon, he introduces the information theoretic foundation and an idea of entropy as a quantity of expressing the information content of a signal [8], [9]. Different methods for audio/speech data compression have been designed in the literature, most of these mechanics exists in classical networks while, limited resources restrict the range of compression methods which can be applied in WSN [10], [11]. Advances in compression for wireless sensors have led to new ways of thinking about approaches to design energy efficient in WSN with low cost data acquisition. Some of the most popular techniques include residual excited linear prediction, code excited linear prediction, mixed excitation, Harmonic coding and Waveform interpolation coding [12], [13]. One of the most adaptive coder in WSN is Linear Predictive Coding. The Linear prediction uses the Linear Self Regression Model. Prediction is based on a Linear combination of the previous samples. This prediction is used for lossless audio compression as SHORTEN design [14], [15]. The predicted is given by equation 1:

$$\tilde{x}(t) = \sum_{i=1}^{P} a_i \, x(t-i) \qquad (1)$$

where the error (difference between the signal and the estimate of the linear predictor) is given by equation 2:

$$e(t) = x(t) - \tilde{x}(t) \qquad (2)$$

The dynamic method consists to compute the a_i coefficients for each frame. Each a_i coefficient is scalarly quantified on seven bits. This ensures a good compromise between prediction quality and storage space. The choice of coefficients a_i is performed iteratively by Levinson-Durbin [16]. The order of the filter is performed at each iteration. At i^{th} iteration, the root mean square error is calculated to estimate the number of bits necessary to encode the filter. Then, the bits required for the filter coding are calculated. Next, add the bits needed to encode the coefficients. Then the order is incremented. The calculation is repeated, and the solution that minimizes the whole is saved. The incrementing of the order stops when the last two rates are higher than the previous ones. The a_i coefficients are quantified, and then coded by Golomb-Rice coding [17].

In [18], the authors proposed an energy saving audio data compression approach for wireless multimedia sensor network using Partial Discrete Cosine Transform (PDCT), where only the last DCT coefficient is propagated thereby saves energy by transmitting and reduced number of bits. The components of the last DCT coefficient are propagated instead of the sensing data.

In [19], the authors proposed an Integer Wavelet Transform to maps integer data set to integer data set. The wavelet transform concentrates audio/speech signals into a few neighbouring coefficients, it is an iterated filter bank that provides a flexible way of analysing a signal at multi-resolution and across multiple frequency regions. Since, wavelet can provide an analysis of the input signal according to the critical band resolution of the inner ear and, more generally, provide an architecture that can adapt to the time-varying nature of the signal.

Alternatively, the authors in [20] proposed to run one lifting wavelet scheme round followed by a dynamic number of differences round, to compute Discrete Wavelet Transforms (DWT) at two stages method (splitting and lifting). The splitting step consists in segmenting the entire data set into odd and even elements. The lifting step consists in involving predict step and update step as described by equation 3 and equation 4 respectively.

$$odd_i = odd_i - \frac{1}{2}\left(\sum_{j \in N(i)} even_j\right) \qquad (3)$$

$$even_i = even_i + \frac{1}{4}\left(\sum_{j \in N(i)} odd_j\right) \qquad (4)$$

where i, j are the node id of odd and even nodes respectively, N(i) denotes the adjacency function of node i.

DWT can be used to extract information from many different kinds of data such as images, videos, vibrations, audio streams along with scalar data, but certainly not limited to extract the informations. The set of complementary DWT are useful in compression and decompression schemes where it is desirable to recover the original data without loss.

3. PROPOSED CODER SCHEME

The proposed method is inspired on DWT, because it is a relatively recent and efficient transformation technique that allows a compact signal representation of time and frequency resolutions. Since human listening is carried out through an analog ear that provides low time resolution with high frequency resolution for low frequency signals and low frequency resolution with high time resolution for high frequency signals. The proposed audio compression approach consists in making perfect, bit-by-bit copies of the perceived sound and using an adaptive lifting scheme to generate wavelet coefficients in sensor network. This to allow a real time signal processing and ensure perfect reconstruction (data after decompression is exactly the same as the original). Hence, the approach ensures perfect sound and also still saves a lot of space. As shown in Figure 1, the first step consists of dividing signal into overlapping analysis frames. The second step consists in removing intra-channel redundancy and temporal redundancy through splitting, prediction and update.

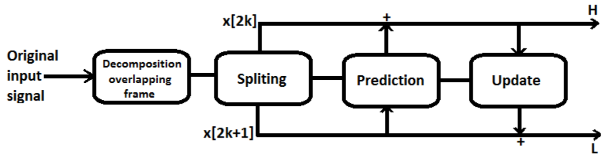

Fig. 1. Proposed lifting structure representation of the wavelet transform for scalable compression system design

3.1 Framing of input signal

In general, audio signals have very rich structures and their properties rapidly change over time. In principle, the signal is composed of infinite samples. In order to make it suitable in real time, it is necessary to cut it into finite samples. To do this, an infinite signal is multiplied by a finite frame size. A natural approach consists of decomposing the signal into a set of overlapping local frames, where its properties remain stable. The following segmentation procedure is used, a suitable sampling address two contradictory requirements which are taken into account when choosing the appropriate frame size. A bigger frame size is desirable to maintain lower bit rates. Unfortunately, a bigger frame size also leads to poorer quality due to the non-stationary of the signals.

This problem is avoided applying an adaptive lifting DWT for extracting non-stationary signals information and analyze their temporal and spectral properties. Thus, segmenting signal into overlapping frames is to divide the signal into frames of length 1024 samples with an overlap of 50%. The splitting step is to decompose the overlapping frames into even and odd coefficients. The lifting step in turn involves prediction step and update step. Thus, each frame is split into segments of K = 16 suitable value at the 44.1 kHz sampling rate, at data samples time interval Ts = 1/(44.1x1024) = 23.22 ms, with 84kb/s bite rate and 1.25e-5 ms execution time per instruction cycle. After partitioning signal into many frames, the next step is to perform spectral analysis.

3.2 Scalable Wavelet transform

Scalable lossless audio coding is an important aspect for many professional applications. When designing the wavelet segmentation, where the signal is divided into overlapping analysis frames, the wavelet transform coefficients are performed iteratively. If subsequent frames are similar enough, a further decomposition is performed. Otherwise, they shall be represented by only one low-pass frame.

The frames are analysed at different frequency bands with different resolutions by using low-pass h(n) and high-pass g(n) filters to expand a digital signal into a coarse coefficients (c_k) and detail coefficients (d_k) as defined by equation 5.

$$\begin{cases} y_{low}(n) = \sum_k x\,(n) g[2n-k]_{n\in Z} \\ y_{high}(n) = \sum_k x\,(n) h[2n-k]_{n\in Z} \end{cases} \quad (5)$$

where y_{low} and y_{high} are the outputs of the high-pass (g) and low-pass (h) filters respectively. c_k provides information about high frequencies and d_k provides information about low frequencies.

Let us denote x_t a coarse coefficient of each scale, x_t is first split into two polyphase components of even (low-frequency) index x_{2t} and odd (high-frequency) index x_{2t+1} components for the horizontal filtering process as shown in Figure 1. The coefficients analysed with a high pass filter are designated with an H and a low pass filter are designated with an L. Temporal filtering is performed by the Le Gall's analysis [21] filter bank and the basic operations to obtain the high-pass filter and low-pass filter. A high-pass filtering in the prediction phase is applied to the input signal which results in the generation of the detailed coefficient designated with an H. While a low-pass filtering in updating phase is applied to the input signal which leads to the generation of the approximation coefficient designated with an L. Then, the sub-bands in lifting form are given by the following equation 6.

$$\begin{cases} H_t = x_{2t+1} + P\left(x_{2(t-k)}\right)_{k\in\mathbb{Z}} \\ L_t = x_{2t} + U\left(H_{(t-k)}\right)_{k\in\mathbb{Z}} \end{cases} \quad (6)$$

Where t denotes the time index, P represents the prediction operator and U an updating operator.

The prediction step consists in approximating each odd coefficient as a linear combination of even coefficients and subtracting this combination from the odd coefficient. The update step consists in modifying the values of the even coefficients by adding to them a linear combination of the odd coefficients already modified. Thus, in the lifting implementation given by equation 7, the high-pass and low-pass outputs are computed using a step-by-step computation and the low-pass and the high-pass output computations take six and eight clock cycles each, respectively. Decomposing a filter into stages reduces the total number of operations required for the transformation and the number of operations is reduced to 4 additions/subtractions and 4 multiplications.

$$\begin{cases} H_t(n) = x_{2t+1}(n) - \frac{1}{2}[x_{2t}(n) + x_{2t+2}(n)]_{n\in\mathbb{Z}} \\ L_t(n) = x_{2t}(n) + \frac{1}{4}[H_{t-1}(n) + H_t(n)]_{n\in\mathbb{Z}} \end{cases} \quad (7)$$

In an environment susceptible of transmitting errors such as wireless sensors networks, the scalability allows the adaptation of the compress flow rate according to the channel capacity, which can vary according to the transmission conditions, and increases the robustness of a coding scheme in case of lossy, errors or congestion. Moreover, scalability is essential in the design of a compression scheme because of the explosion of multimedia applications and the growing need to broadcast content to heterogeneous receivers. Thus, scalability property makes it possible to broadcast a single compressed stream, which can be adapted by the nodes of a network or decoded by a wide variety of receivers. So that, the even frames are left unchanged, and it has become the input for the next step in the transform and the even and odd sequences are modified by alternately applying prediction and update operations. Thus the scaling function is defined by equation 8.

$$\begin{cases} H_t(n) = \frac{\sqrt{2}}{2} H_t(n), n \in \mathbb{Z} \\ L_t(n) = \sqrt{2} L_t(n), n \in \mathbb{Z} \end{cases} \quad (8)$$

Hence, the optimal quality scalability is effectively achieved. In the coding scheme, the coefficients are coded in decreasing order of their importance with reduced precision. The lifting formalism guarantees the invertibility of the compression scheme and therefore the original signal x can be perfectly reconstructed using the same lifting steps in reverse order by undoing the update and predict steps as defined by equation 9. During the decoding process, the signal is first approximated by the most significant coefficients and then gradually refined by the least significant coefficients.

$$\begin{cases} x_{2t}(n) = L_t(n) - U(H_t\,(n))_{n\in Z} \\ x_{2t+1}(n) = H_t(n) - P(x_{2t}(n))_{n\in Z} \end{cases} \quad (9)$$

4. IMPLEMENTATIONS AND EXPERIMENTATIONS

In this work, the wireless multimedia sensors show in Figure 2 were used to collect audio information from the environment and transmits through the wireless networks (Zigbee) to a central sink node or Personal Computer (PC), for processing or storage.

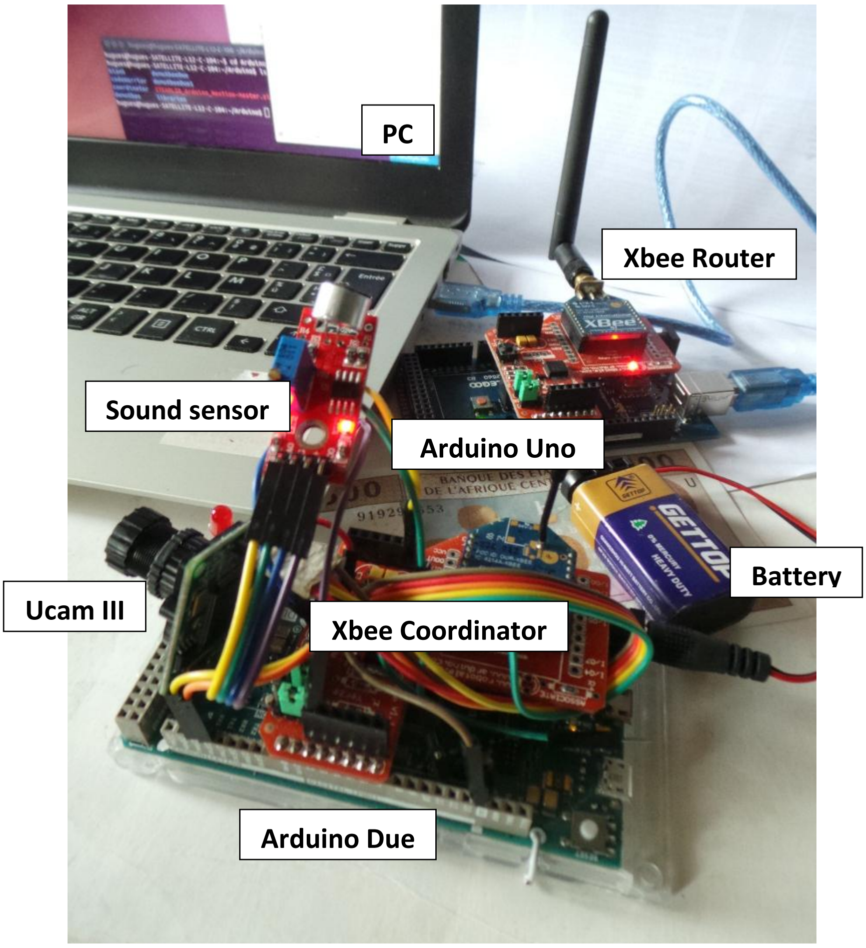

Fig 2: Proposed WMSN implemented using Arduino modules

The architecture shown the Figure 2 above is constructed from the Arduino due board AT91SAM3X8E with 512 kB of flash memory and 100 kB of SRAM, 80 MHz Clock, XBee S1 802.15.4 module connected to ArduinoxBee shield at 125000 bauds. The Arduino MEGA2560 R3 with 256 kB of flash memory and 8 kB of SRAM, 16 MHz Clock, XBee S1 802.15.4 module connected to ArduinoxBee shield at 125000 bauds. The sensing device (microphone), camera ucamIII and others input peripherals (UART, SPI, CAN, ADC, LED, APPLICATION, etc) are located on Arduino due board. One Ultralife Lithium 9 V battery, 1200 mAh, 38880 J. The gateway is built on the Linux operating system (Ubuntu 14.04). The compression scheme is developed using C++ language code, on PC Intel(R) core TM i5-2520M processor @ 2.50 GHz, RAM: 8 GB.

5. RESULTS AND EVALUATION PROCESS

The sets of experiments are conducted for evaluating the performance of the proposed approach and to compare the results with standard DWT and DCT scheme [18].

Testing was performed from Arduino due board, a recording of 10 minutes of the Movie was used for experiment purposes, and transferred to the base station (PC) via Zigbee wireless communication. A wave (.wav) file has been created extracting the audio from the dataset.

The evaluation process consists in measuring the Compression Ratio (CR), the difference between the input and output signals (Percentage Root-mean-square Difference) and energy saving [22]. The Compression Ratio is defined by equation 10:

$$CR(\%) = \frac{S_{comp}}{S_{orig}} x100 \qquad (10)$$

where S_{comp} denotes the size of the compressed data, and S_{orig} is the size of the original data.

To measure the reconstruction distortion, the Percentage Root-mean-square Difference (PRD) is given by equation 11:

$$PRD(\%) = \sqrt{\frac{\sum_{n=0}^{N-1}[S_{orig}(n) - S_{decomp}(n)]^2}{\sum_{n=0}^{N-1} S_{orig}^2(n)}} x100 \qquad (11)$$

where S_{orig} represents the original signal, S_{decomp} the reconstructed signal, and n represents the number of samples.

The percentage of gain is given by equation 12.

$$Gain(\%) = \frac{B_s}{B_t} x100 \qquad (12)$$

where B_s denotes the number of bits saved and B_t the number of bits transmitted without encoding.

The Energy consumed (E_c) is given by equation 13. The main operations that consume energy of a sensor node are computing and data transfer.

$$E_c(mJ) = Volts(V) \times Amps(mAh) \times Time(s) \qquad (13)$$

where, E_c denotes the energy consumed in milli-joules, Volts the voltage of the discharge storage system in volt, Amps is the current capacity of discharge in milli-ampere-hours and Time represent the duration of discharge (runtime) in seconds.

The compression scheme runs in 4 additions/subtractions and 4 multiplications, then the pipeline is 8-cycle long. The CPU starts an instruction, and that instruction will be finished at T_i = 8x1.25e-5 ms = 1e-4 ms later. The execution time $T_i < T_s$, hence no data sample is missed during the process. Table 1 shows the CR, PSD, Ec and processing Time comparison.

Table 1. Comparison of CR, PSD, Ec and Time of existing methods with proposed approach

Metric calculated	DCT approach	Standard DWT	Proposed approach
CR (%)	**36**	32.6	27.6
PRD (%)	2.9	2.4	**2.17**
Ec (mJ)	74155.8	50362.3	**49004.2**
Time (s)	58.32	**45.64**	49.58

The experimental results in Figure 3 shows that, with 1024 samples, DCT approach, presents a better Compression Ratio (CR) than the proposed approach. By contrast, the proposed approach has improved a better performances than DWT (Discrete Wavelet Transform) [20].

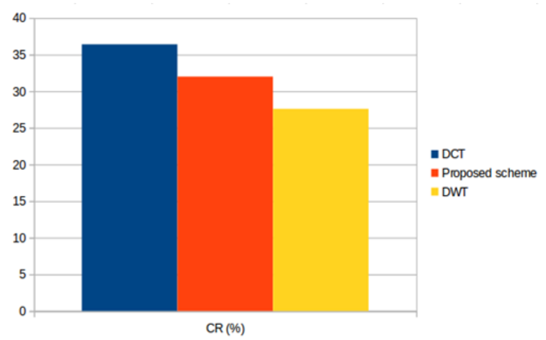

Fig. 3. Comparison of Compression Ratio (CR) in percentage

On the other hand, the proposed approach presents the better Percentage Root-mean-square Difference (PRD) than DCT as shown in Figure 4. Hence, the proposed encoding scheme saved 32.6 % of storage.

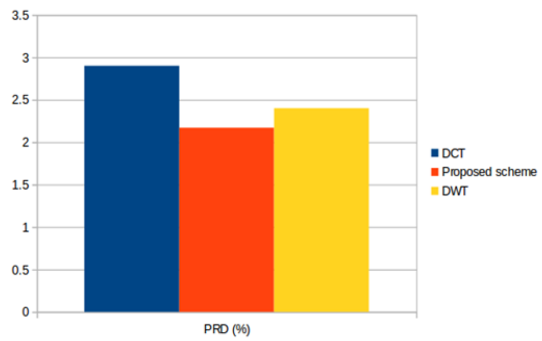

Fig. 4. Comparison of Percentage Root-mean-square Difference (PRD) in percentage

The typical current consumption of the sensor in processor computing and radio transmission of the proposed approach is 104 mAh, the average operating voltage is 4.3 V, and the average time of operating 109.58 s is better than DCT and DWT as shown in Figure 5.

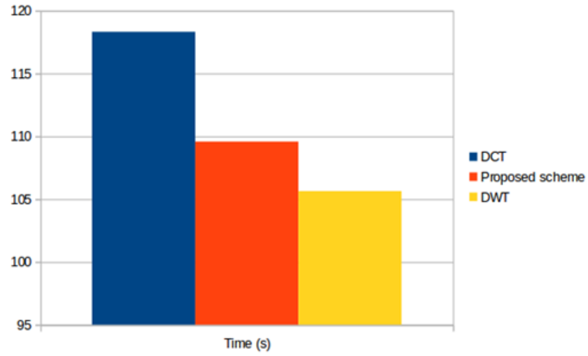

Fig. 5. Comparison of average time operating (Time) in seconds

Thus, the average energy consumption of the proposed approach given by: E_c = 4.3V x 104mA x 109.58s = 49004.176 mJ is better than the comparative approaches (DCT, DWT and the uncompressed transmission) as shown in Figure 6. Without compression, the process consumed 102433.479 mJ. Hence, 47,84% of energy is saved. So, the proposed scheme consumes much less energy compared to its competing schemes.

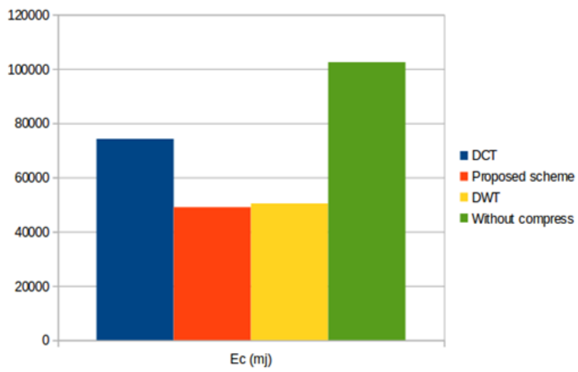

Fig. 6. Comparison of Energy Consumed (Ec) in MilliJoule

6. CONCLUSION AND FUTURE WORK

The purpose of this research work is to propose and evaluate a low-resources hardware-based audio data compression architecture in Wireless Multimedia Sensors Networks (WMSN). In this paper, wireless sensor has been used for recording and transmitting audio data. However, because of the limited amount of resources (power, low-capacity of radio waves, bandwidth, memory, processing, storage, etc) available in WSN, a proposed method that has to be considered to save resources is the data compression of the transmitted data. Thus, only methods possessing low CPU and memory requirements could be applied. The proposed hardware encoding solution aims to adapt the discrete wavelet transform in order to exploit the correlation in sensing data. The experimental results compared to existing state-of-the-art schemes demonstrate that the proposed approach successfully compresses the sensing data and achieved significant energy savings without losing quality of the data reconstruction.

As a future extension of this work, the proposed scheme may be improved upon by being able to correctly detect and handle scene-cuts and scene changes.

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8. CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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