Video Encoding for Wireless Multimedia Sensor Networks: A Review

Vusi Skosana[1]
[1]Department of Electrical,
Electronic and Computer Engineering,
University of Pretoria,
Pretoria, South Africa
Email: vskosana@csir.co.za

Adnan M. Abu-Mahfouz[1,2]
[2]Council for Scientific and Industrial
Research (CSIR),
Pretoria, South Africa
Email: a.abumahfouz@ieee.og

***Abstract*—Wireless multimedia sensor networks (WMSNs) make possible diverse and demanding monitoring and surveillance applications. The WMSNs have to operate with significant energy, memory and processing power constraints. These constraints make video encoding vital but challenging to accomplish. Many approaches have been attempted but each one comes with its shortcomings. In this paper, a framework was developed to compare and contrast different methods for video encoding in WMSNs. This allows both researchers and practitioners to evaluate the different trade-offs that current techniques entail and what research gaps are not being addressed.**

***Index Terms*—wireless sensor networks, wireless multimedia sensor networks, video encoding, image compression, compressive sensing**

I. Introduction

Wireless Multimedia Sensor Networks (WMSNs) are self-organising systems of embedded devices deployed to fetch, process and collate multimedia streams from dissimilar sources [1]. WMSNs make possible novel applications such as video surveillance, storage, and recovery of actions and locations of people [2]. Unlike conventional wireless sensor networks, WMSNs need to avail multimedia with a deterministic level of quality-of-service (QoS) [3]. This requirement entails advanced data compression for lessening the bandwidth and energy utilisation of the sensor nodes [4].

A WMSN is made up of a number of optical sensor nodes that are deployed to a field of interest along with one or more data sinks at the centre or remotely [3]. The optical sensor nodes capture the scene at different locations in the field and send their observations to one or more sinks. The camera node can be connected to the data sinks through multi-hop routing, which increases the importance of a good compression ratio.

Significant research and substantial progress have been realised in solving many wireless sensor networking challenges, the fundamental problem of real-time quality-aware video streaming in large-scale, multi-hop, wireless networks of embedded devices remains open [5]. In particular, the development of video encoders that can realise the performance enjoyed from internet streaming on the more challenging wireless networks. In [6], Pudlewski *et al.* list four challenges that the designers of video encoders for WMSN have to overcome; data rate constraints, complexity constraints, channel conditions and network constraints.

Encoder complexity and poor resilience to channel errors are the two important limitations of systems based on the transmission of predictively encoded video through a layered wireless communication protocol stack [7]. Compressed Sensing (CS) was proposed by Pudlewski *et al.* [2] as the solution to overcoming these challenges. CS allows for under-sampling of sparse signals through an encoder with little complexity. The application of image acquisition and reconstruction using CS faces many obstacles. The reduction of computational cost and sampling rate are the principal obstacles of compressive imaging [8].

Traditional compression and compressive sensing are the two primary approaches to video encoding in WMSN. Each of the approaches has strengths and weaknesses. Many researchers have done work to address some of the challenges encountered with each approach. However, choosing which approach to use when designing or applying video encoding in WSMN is a challenging problem. There exist many metrics by which video encoding is measured, these include compression ratio, image quality, energy consumption, throughput and memory requirements. To homogenise and streamline the review, this paper focuses on image quality and energy consumption. Image quality is measured using Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM), the latter being more consistent with human eye perception [9]. In this paper, some of the most significant approaches to video encoding are reviewed. A framework was developed to compare and contrast different methods to establish what are the main benefits and disadvantages of each method. This allows both researchers and practitioners to evaluate the different trade-offs that current techniques entail and what research gaps are not being addressed.

In Section II research output on video encoding is reviewed while in Section III the different approaches are compared and then discussed. The paper is concluded and future work proposed in Section IV.

II. Video Encoding

A. Traditional Compression

The JPEG standard is the most frequently used lossy compression scheme. To perform compression, a discrete transform is applied to image data. The transform coefficients are quantised and entropy coded before forming the output code stream [10]. The compression process is shown for the encoder and decoder in Fig. 1. The quantisation of the transform coefficients is where the information is lost. The compression rate can be traded-off for how much information is retained during quantisation. This compression scheme has been widely used in WMSN applications. Researchers primarily try to optimise it by improving the computational efficiency of the DCT, which is the most expensive part of the pipeline. Other transforms have been used, such as DWT. Because of the difference in how the transforms work, some modifications are applied to the pipeline, see Fig. 2 and 3.

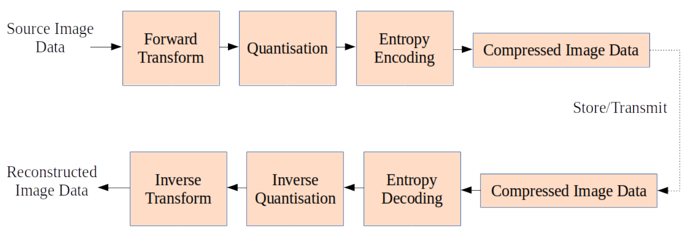

Fig. 1. The JPEG compression pipeline [10].

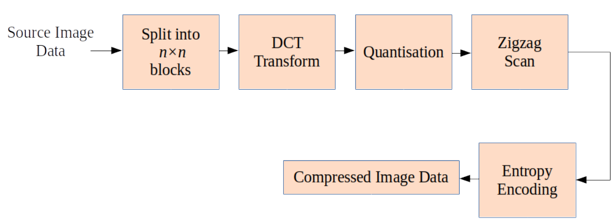

Fig. 2. The DCT encoder [11].

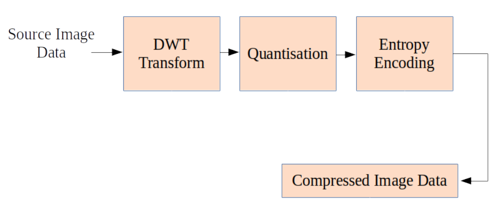

Fig. 3. The DWT encoder [11].

Mechouek *et al.* [12] aimed to reduce the energy consumption of the JPEG standard. The authors proposed to reduce the computational complexity of the 8-point DCT transform. The DCT computation is the most expensive part of the JPEG pipeline. They aimed to solve the lack of orthogonality and the low energy compaction in previous approximations, that led to low compression efficiency. To this end, they proposed a low-complexity DCT approximation which consists of the combination of rounding and pruning approaches. Their DCT approximation is tested in the JPEG compression chain against other DCT approximations. They used WinAVR on Atmel ATmega128L hardware platform to perform their experiments with 512 $\times$ 512 8-bit standard greyscale images. The authors evaluated image quality using PSNR and energy consumption using computation cycles per 8 $\times$ 8 block on the Atmega128L. Their implementation performed the best in terms of image quality and energy consumption.

Wei *et al.* [13] attempted to improve image quality without compromising compression ratio. The authors also tried to balance the energy consumption of the network through a distributed multi-node cooperative network model. The authors introduced a variant of PCA compression called noise-tolerant distributed image compression. They compared their algorithm against JPEG2000 [14] and block cooperative SVD [15]. The authors used MATLAB to perform simulations with 512 $\times$ 512 8-bit standard greyscale images. The authors compared image quality using PSNR and energy consumption of the transmission and reception of the images but not of the compression. Their implementation performed better than the other methods in terms of energy consumption and image quality.

Sheltami *et al.* [11] noted that there are many compression algorithms inapplicable for the real-time environment because of memory usage, energy consumption and processing time. To overcome these challenges, they proposed and evaluated the DCT and DWT image compression schemes because of their ease of implementation. With their choice of compression schemes, the authors made a trade-off between compression ratio and energy consumption. They compared the performance of the two compression schemes using various metrics. The authors used the TelosB platform with TinyOS to perform their experiments. They applied the different compression techniques to the Lena 8-bit greyscale images of resolution 32 $\times$ 32, 64 $\times$ 64 and 128 $\times$ 128. They measured image quality using PSNR and energy consumption by execution time for compressing 32 $\times$ 32 image. The authors found that DWT performs better in terms of image quality and energy consumption. However, the DCT performed the best in terms of compression ratio.

Araar *et al.* [16] attempted to extend the lifetime of WMSN camera nodes by making improvements to the energy consumption of 8-point DCT approximations. The authors applied pruning even further to a DCT approximation. The authors investigated the computation cycles, processing time, energy consumption and image quality. They compared their approximation against the state-of-the-art approximations, including [12]. The authors used WinAVR simulations on Atmel ATmega128 based platform with 512 $\times$ 512 8-bit standard greyscale images. They evaluated image quality using PSNR and derive energy consumption from computation cycles per 8×8 block of pixels. Their algorithm gave the best energy consumption but had slightly lower image quality than [17].

Kouadria *et al.* [18] proposed replacing the DCT in traditional image compression with its alternative, the discrete Tchebichef transform (DTT) to eliminate the computational cost of the former. The DTT has good energy compaction, low algorithmic complexity and low memory requirements. The authors pruned the DTT to further improve it's complexity and memory requirements. They then compared the 8-point DCT, exact DTT and pruned DTT against each other. The authors used the Mica2 platform with the Atmel ATmega128 microcontroller. They used the standard 8-bit greyscale images in 256×256 and 512×512 resolutions. The authors measured image quality using PSNR and SSIM, while energy consumption was derived from the number of operations required for every 8×8 block of pixels. The pruned DTT performed the best in terms of energy consumption but had worse image quality than the DCT and exact DTT. The exact DTT and pruned DTT could be investigated further as sparsity transforms for compressed sensing approaches.

Kong *et al.* [19] attempted to overcome the issues of low image quality and high energy consumption in WMSN. The authors wanted to solve the weak topology design of JPEG2000 [20] and image artefacts from SVD [15] distributed compression schemes. They proposed an image compression scheme based on non-negative matrix factorisation (NMF). The authors also proposed a collaborative mechanism for image acquisition, blocking, compression and transmission. They compared their algorithm against JPEG2000 and SVD using MATLAB simulations using 8-bit greyscale images with a resolution 512×512. The authors measured the image quality using the PSNR but did not measure the energy consumption of the compression, focusing instead on the network energy consumption and load balancing. They found that their algorithm gave better image quality and energy consumption.

Patel and Chaudhary [21] noted that data collection, processing and transmission take up a large amount of energy in WMSN. To lessen the energy consumed by processing and transmission they proposed improving image compression. The authors added SVD to DWT-DCT hybrid compression [22] to save energy by improving the compression rate. The authors also attempted to balance energy consumption in the network through node clustering and distribution of image compression. They compared their approach with the DWT-DCT hybrid implementation. They used MATLAB to perform their simulations on colour images of size 512×512. They measured image quality using PSNR and reported the per-bit energy consumption of their compression algorithm against the existing method. Their approach entailed lower energy network cost at the price of moderately lower image quality.

Coutinho *et al.* [23] proposed the pruning of DTT approximations to improve energy consumption and bandwidth utilisation. The authors pruned state-of-the-art low-complexity 8-point DTT approximation to further reduce complexity. They exploited the low-complexity characteristics of the direct pruned transformation matrix by adopting the transposed pruned matrix as an approximation for computing the inverse transformation. They compared their implementation with exact DTT and other approximations using different values for the pruning parameter, K. They used Xilinx Virtex-6 FPGA device with Xilinx ISE to perform experiments. The authors measured image quality using PSNR and SSIM, they measured energy consumption using the area-time (AT) and area-time-square (AT^2) FPGA figures of merit. Their implementation gave the best energy consumption at the price of worse image quality.

Banerjee and Bit [24] acknowledged the trade-off between computation and transmission cost accompanied by algorithms such as DWT and DCT. The authors proposed curve-fitting to overcome this challenge. They evaluated linear and polynomial fit variants of curve-fitting compression. They applied the compression techniques after partitioning the image into macroblocks. The authors used ContikiOS on MicaZ platform with an Atmel ATmega128 microcontroller to carry out experiments. They compared their implementation with state-of-the-art schemes using PSNR and SSIM for image quality and average energy consumption per image. They achieved the best energy consumption from both curve-fitting compression variants but had slightly worse image quality than DCT and partial DCT.

In [25], Araar *et al.* introduced a pruned DCT approximation that requires only ten additions. The authors reduced the computational complexity of the 8-point improved DCT approximation [26] by pruning the higher frequency coefficient. They developed a fast algorithm to compute the transform based on sparse matrix factorisation. Their method requires ten additions for forward and backward transformations. The authors evaluated their algorithm on Xilinx Virtex-6 FPGA device using Xilinx ISE. The authors used a set of 45 standard 8-bit greyscale images of resolution 512×512 to test their algorithm. The PSNR and SSIM were used to measure image quality and the AT and AT^2 were used to measure energy consumption. Their algorithm gave the best energy consumption but performed slightly worse than [26] on image quality.

B. Compressive Sensing

Compressive sensing has attractive features for application in WMSN, lower complexity, high compression rate and channel error resilience [27]. Compressive sensing requires the input signal to be sparse before application [28]. The signal can be made sparse using domain transforms. Once the signal is sparse, it is packed into a sparse vector. The sparse vector is made up of non-zero values that indicate the degree of sparsity of the vector. The measurement matrix is derived from computing the minimum number of measurements needed for recovering the original signal. The measurement matrix is used on the sparse vector to acquire the measurements. The encoder and decoder pipeline can be seen in Fig. 4.

Nandhini *et al.* [28] proposed the use of compressive sensing to overcome the challenge of large storage and bandwidth

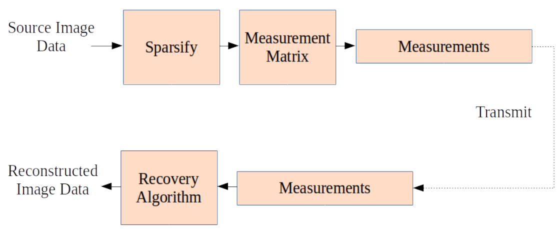

Fig. 4. The CS pipeline [28].

requirements in WMSN. They divided the image into macroblocks and then applied DWT, DCT and DWT-DCT hybrid transforms to make the macroblocks sparse. The authors also proposed two memory efficient measurement matrices. They evaluated these different approaches using the TelosB platform with ContikiOS. The first four frames of size 240 $\times$ 320 from a xylophone, akiyo and football video sequences were used. The authors measured PSNR to assess image quality. The DWT-DCT implementation was shown to be the best in terms of image quality and compression rate. The authors further found that their measurement matrices outperformed the Gaussian matrix in terms of power consumption and image quality. However, the authors only measured energy consumption from generating the measurement matrix and transmission of measurements but not of the calculation of the transforms.

In [27], Angayarkanni and Radha attempted to lower the sampling rate of signals in WMSN to improve real-time performance. In conventional CS, the measurements are transmitted and reconstructed using CS recovery algorithms. The authors proposed CS-based prediction measurement encoder to reduce the number of measurements further to reduce storage space and bandwidth requirements. The authors used DWT and DCT to obtain sparse transforms and the Gaussian measurement matrix. They compared the algorithm against other encoders using TelosB hardware with ContikiOS. The akiyo, Foreman and news YUV sequences in CIF format with dimension 288 $\times$ 352 video sequences were considered. The authors measured PSNR and SSIM to assess image quality. The results showed that the method achieves a large compression ratio at competitive image quality.

Zhang *et al.* [29] took advantage of the relative computational efficiency and channel resilience of CS. To improve the computational efficiency of adaptive block compressed sensing, they proposed the use of standard deviation to assign sampling rates. The method consisted of first assigning a fixed sampling rate to each block then an adaptive sampling rate being assigned based on the standard deviation. The authors constructed the sensing matrix based on the sampling rate assignments. The final measurements were obtained by concatenating the fixed and adaptive measurement. They evaluated their algorithm against unaltered block compressed sensing using experiments in MATLAB. They used standard 8-bit greyscale images with 512 $\times$ 512 resolution using PSNR to measure image quality. At high sampling rates, their implementation had much better image quality but at low sampling rates, their implementation had slightly lower image quality.

In [30], Banerjee and Bit attempted to leverage the strengths of DCT and compressed sensing. They argued that DCT transform provides low-overhead compression while compressed sensing ensures reconstruction with few measurements. They replaced the DCT with a partial DCT to obtain a sparse transform of the image. The authors explored the Gaussian and binary measurement matrices to further reduce data size. They used the ContikiOS on the MicaZ platform with the Atmel ATmega128 to perform the evaluation. They measured PSNR and SSIM to assess image quality and the computational energy consumption is calculated from the instruction cycles for all the frames of the input video. Their implementation gave the best performance in energy consumption against the state-of-the-art techniques but performed worse in terms of image quality than multiview video coding [31] and the partial DCT without compressed sensing.

In [32], Nandhini *et al.* aimed to improve the efficiency of compressive sensing. The authors exploited the properties of Toeplitz matrix structure of lower computational and storage complexity. They proposed a new sensing matrix that combines Toeplitz, Hankel and circulant matrices. The proposed matrix was designed using the Toeplitz matrix with Gaussian entries as the basis. The Toeplitz matrix was generated using the Gaussian entries to achieve higher image quality. The authors used DCT to obtain a sparse transform of the image blocks. They compared their sensing matrix to the Gaussian using TelosB hardware with ContikiOS. The authors considered standard 8-bit greyscale images of resolution 128 $\times$ 128. The PSNR and SSIM were measured for image quality while the energy consumption was measured for generating the measurement matrices. They found that their energy consumption is lower while their image quality is higher than the Gaussian sensing matrix.

III. Comparison and Discussion

In traditional image compression, the focus has been on improving the computational complexity of the DCT. The researchers in [12], [16], [25] focused on improving the complexity of the DCT and achieved improvements but with a sacrifice of image quality. Other researchers have replaced the DCT with an equivalent transform, the exact DTT and its approximations [18], [23]. A hybrid of the DCT transform has been proposed [21]. Other researchers have used more uncommon transforms such as in [13], [19], [24]. The trend is that lower energy consumption leads to lower image quality, as seen in Table I. However, these studies are carried out with different test images, hardware and energy consumption metrics making it difficult to make a direct comparison.

Most of the compressed sensing approaches have been using the DCT transform and optimising other aspects of the compression algorithm, with the exception of [28]. In [28],

TABLE I
COMPARISON OF VIDEO ENCODING APPROACHES

Ref.	Approach	Transform	Focus	Strengths	Shortcomings
[12]	Traditional	DCT	They authors aimed to solve the lack of orthogonality and the low energy compaction in previous DCT approximations	Good image quality and energy consumption compared to other DCT approximations	The DCT approximations are still relatively computationally expensive.
[13]	Traditional	PCA	Overcoming the trade-off between image quality and compression ratio	The PCA compression had good image quality results compared with JPEG2000 [14] and SVD [15]	The PCA is computationally expensive and will have high relative energy consumption.
[11]	Traditional	DWT	The authors traded-off compression ratio for energy consumption	DWT has better image quality and energy consumption	The DCT has higher compression ratio than DWT.
[16]	Traditional	DCT	Improving the energy consumption of DCT approximations	The DCT approximation has lower energy consumption compared to state-of-art methods	The DCT approximation has slightly lower image quality [17]
[18]	Traditional	DTT	Replacing the DCT with lower complexity DTT and pruned DTT	The energy consumption was the best on the pruned DTT	The pruned DTT had lower image quality than the DCT and exact DTT
[19]	Traditional	NMF	Solving to solve the weak topology design of and image artefacts from distributed compression schemes	Higher image quality and lower energy consumption than JPEG2000 [20] and SVD [15]	The compression scheme relies on node collaboration and will be sensitive to channel noise and link length.
[21]	Traditional	SVD-DWT-DCT hybrid	To reduce energy consumption from processing and transmission by improving image compression rate	Lower energy consumption than DWT-DCT hybrid [22]	Lower image quality.
[23]	Traditional	DTT	Improving energy consumption through lowering computational complexity of the DTT approximations	Lower energy consumption than other DTT approximations	Lower image quality than other DTT approximations
[24]	Traditional	LCF/ LCF	Overcoming the trade-off between transmission and computation cost of DCT and DWT compression	Low energy consumption	Lower image quality than the DCT and partial DCT
[25]	Traditional	DCT	Pruning DCT approximations	Low energy consumption	Lower image quality than [26]
[28]	Compressed Sensing	DWT-DCT hybrid	Improving storage and transmission requirements for image data	Higher image quality and compression ratio than the DWT and DCT, the measurement matrices also had higher image quality and lower energy consumption than the Gaussian matrix	The calculation of the DWT and DCT will negatively affect the energy consumption of the system.
[27]	Compressed Sensing	DCT/ DWT	Encoding compressed sensing measurement to reduce the number of measurements further so as to reduce the storage and bandwidth requirement	High compression ratio and competitive image quality	The DCT and DWT transforms negatively affect the power consumption of the camera nodes.
[29]	Compressed Sensing	DCT	Improving the computational efficiency of adaptive block compressed sensing	High image quality at high sampling rates	Low image quality at low sampling rates
[30]	Compressed Sensing	DCT	Effectively exploiting the strength of the partial DCT and compressed sensing	Low energy consumption	Lower image quality than the partial DCT without compressed sensing
[32]	Compressed Sensing	DCT	improving the efficiency of compressive sensing measurement matrices	Lower energy consumption and higher image quality than the Gaussian matrix	The computation of the DCT transform places a significant energy consumption burden on the camera node

the authors experimented with different transforms and found a DWT-DCT hybrid to be the best in terms of compression ratio and image quality. Improving the sensing matrix has attracted attention in [28], [32] with attractive benefits, where energy consumption can be improved without sacrificing image quality. In [30] they exploited an optimised DCT and achieved lower energy consumption but at a cost of lower image quality. Another focus has been on improving the efficiency of adaptive sensing by using standard deviating to assign sampling rate, leading to lower energy consumption at the price of image quality [29]. In [27] they proposed an encoder to further reduce measurement from compressed sensing with lower image quality.

IV. Conclusion

In WMSN, traditional compression techniques have been widely used. The most common adaptation to applications in WMSN is reducing the computational complexity of the DCT. This techniques reduces energy consumption from compression but comes at the price of lower image quality. Other work on traditional compression has been increasing the compression ratio at the expense of more computational complexity. This trade-off is attractive in multi-hop environments where transmission cost saving could offset the computational cost. The compressive sensing approaches are more suitable for WMSN applications. The compressive sensing approaches are less complex, energy efficient and resilient to transmission errors. Furthermore, various authors have shown that compressive sensing can be made more energy efficient without compromising image quality. However, compressive sensing compression still has a lot of scope for improvement. More work needs to be done to evaluate energy efficient transforms and low complexity approximations to further reduce energy consumption. Work needs to be done to test all these techniques using the same hardware, test images and metrics to have a quantitative comparison.

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