ARTICLE IN PRESS

Ain Shams Engineering Journal xxx (2018) xxx–xxx

Contents lists available at ScienceDirect

Ain Shams Engineering Journal

journal homepage: www.sciencedirect.com

Energy efficient image coding techniques for low power sensor nodes: A review

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ARTICLE INFO

Article history:
Received 8 November 2016
Accepted 19 October 2017
Available online xxxx

Keywords:
Image compression techniques
DCT
DWT
Wireless sensor networks
VSN
Entropy coding

ABSTRACT

Visual Sensors Networks (VSN) are spatially dispersed distributed networks, consisting of small sensing units and image sensors. They are scattered over a region to sense, collect and transfer data and are involved in domains such as environmental monitoring, surveillance and tracking. The resource restrictions imposed on sensor nodes are the challenges for image transmission. Sensor nodes are battery power supplied. The greatest operative solution is image compression for energy efficient image communication. With the advent of VSNs, energy-aware compression algorithms have gained wide attention. Since the application of the conventional standards are not energy beneficial. New strategies and mechanisms for power-efficient image compression algorithms are developed. The scope of this review is to provide a holistic review of such energy efficient image compression algorithms for camera equipped VSN. This survey enumerates the benefits and limitations of conventional image compression standards to latest compression technique developed and adapted for VSN.

1. Introduction

Wireless VSN are spatially dispersed networks consisting of small sensing devices fortified with low-power CMOS imaging sensors such as Cyclops. Ideally, WSNs are deployed in the region of interest to collect and transmit data in multi-hop way. Sensor nodes are involved in many domains such as environmental monitoring, video surveillance, and object detection and tracking [1,2]. The sensor nodes are resource limited. The resource constraints in computation, memory, bandwidth and energy are the major challenges to sensor network designs especially for image transmission. Hence forth energy-aware compression algorithms dedicated for VSN have gained wide attention. That is, new strategies and mechanisms for power-efficient image compression algorithms are developed, since the application of the conventional methods is not always energy beneficial.

The compression algorithms will reduce redundancies and hence will reduce the size and lower the bandwidth requirement while preserving acceptable image quality of reconstructed image. The compression techniques are broadly categorized into lossy and lossless compression techniques. In lossy compression, certain amount of information is discarded and hence some data is lost. The lossy compression techniques have high compression ratio with low image quality. The lossless techniques will have low compression ratio but the image quality is highly closer to the original. The lossy compression techniques are most suitable for the resource constrained VSNs. The schematic image compression model could be as in Fig. 1.

The choice of choosing the best compression technique depends upon the nature of system. One of those operating platforms is visual sensor network (VSN). VSN consists of a number of low cost camera sensor nodes arrayed in a region of interest with one or more base stations or sink nodes as depicted in Fig. 2 to sense the physical phenomenon. Each VS (Visual Sensor) node in VSN has the ability to capture, compress and communicate the vision data to the sink nodes. The sink nodes are the network manager or controller [3]. The sink node controls and coordinates the functions of the other nodes. It also aggregates information gathered from the nodes to be stowed or further managed.

VSN has widespread applications like surveillance (military, on road traffic), environmental monitoring (industrial process controlling, machines), habitat monitoring (kids, elderly persons), security monitoring, health care, critical infrastructure protection, chemical and biological detection, plant monitoring, agriculture, animal tracking [4–6]. In addition, with camera sensors, the VSN faces new challenges compared to conventional scalar WSN. The major challenges of VSNs are the following points [7–10].

Peer review under responsibility of Ain Shams University.
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https://doi.org/10.1016/j.asej.2017.10.004
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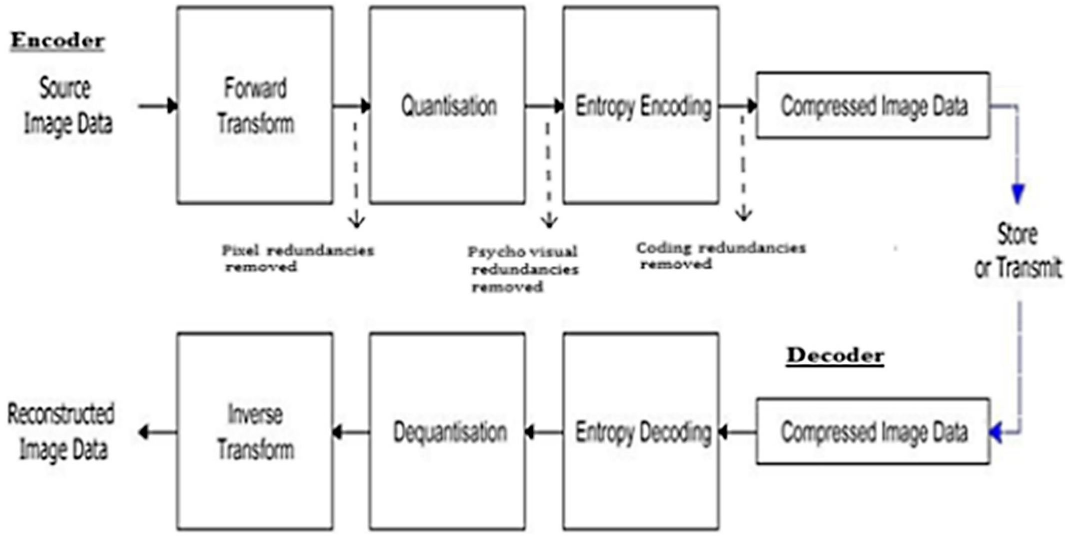

Fig. 1. Image compression model Encoder and Decoder.

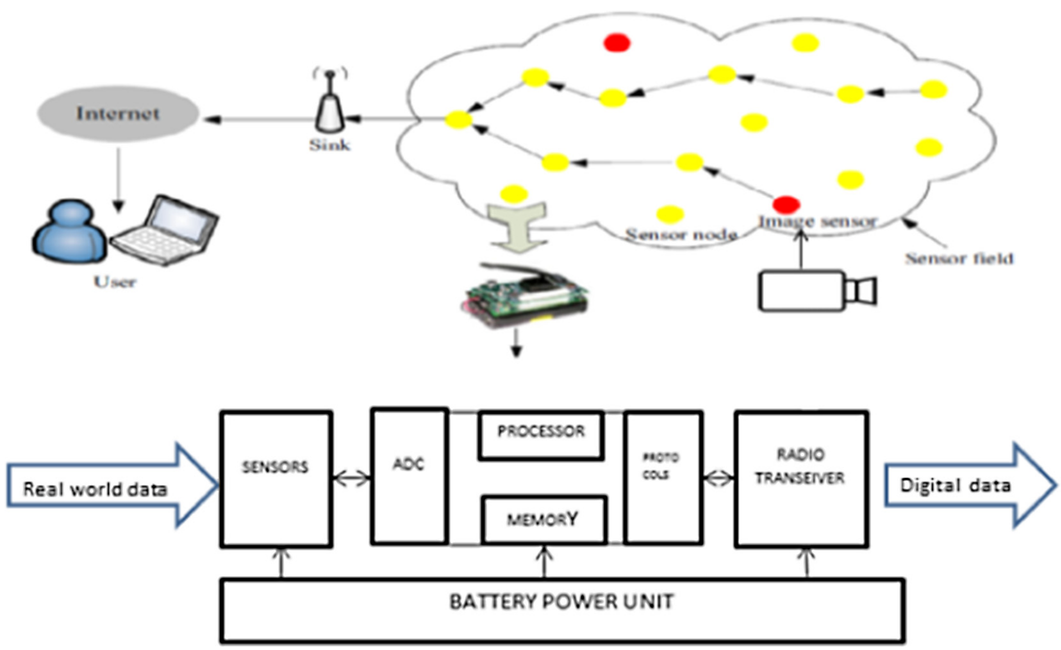

Fig. 2. Typical VSN architecture and sensor mote modules.

1. Bandwidth constraint - Communication of single image requires more number of data packets.
2. Processing capability constraint- Camera nodes and forwarding nodes deplete their energy faster.
3. Power constraint- The transceiver is the most power avaricious electronic component of sensor node.

Typically, compression is performed by exploiting pixel correlation and by reducing pixel redundancies. The main objective of this review is to study and analyse substantial research guidelines in this topic. It concludes the benefits and limitations of most recent efforts of state of the art as well as open research challenges for each compression method and their adaptability to VSN. Low complex image compression techniques will consume less power thus permitting long lifetime of camera nodes in the network which is the main performance metric of VSN. Moreover, this paper explores various hardware platforms, which permit implementation of energy efficient image compression techniques. For example, the time taken to perform 2D- DWT (daubechies 5/3 filter bank) on a 8 bpp image of size 128×128 by ATmega128L microcontroller is around 8 s and time taken by the same microcontroller with Cyclops image sensor and with its typical operating frequency of 7.3728 MHz to perform 2D- 8×8 Loeffler DCT is around 7 s [11,12]. The Table 1 lists some of the available hardware platforms [10,13–15] for better realization of resource restrictions in the VSN.

The paper is structured as follows: Section 2 discusses the performance metrics of image compression algorithms. Section 3 elaborates two broad paradigms of compression techniques i.e., transform based and non-transform based compression techniques Section 3.3 debates on Discrete Cosine Transform based algorithms, which is used in popular JPEG (Joint Photographic Experts

Table 1
Visual Sensor Network Platforms.

Platform	Processor	Internal memory	External memory	Mote interfacing	Radio Module	Imager
CYCLOPS	ATMEL ATmega128L	64 KB	512 KB	Mica2	TR1000 (40 kbps)	ADCM-1700
CITRIC	PXA270	64 MB	16 MB	Tmote Sky mote	CC2420 (250 kbps)	OV9655
Panoptes	Intel XScale PXA255	64 MB	32 MB	COTS hardware	IEEE802.11	Logitech USB Camera
MeshEye	ATMEL AT91SAM7S	64 KB	256 MB	Fully integrated	CC2420 (250 kbps)	Agilent ADNS-3060
Vision Mote	ATMEL 9261 ARM 9	64 MB	128 MB	Fully integrated	CC24309 (250 kbps)	CMOS Camera (unspecified)

Group) compression standard. Section 4 illustrates about Discrete Wavelet Transform based coding techniques, which is used in popular JPEG2000 image compression standard. Section 5 discusses about various lossless entropy coding schemes flexible for VSN. Under Section 6, energy consumptions of various image compression techniques available in the literature is summarized and Section 7 concludes the paper by presenting open research issues and limitations.

2. Performance metrics

The performance of any image compression algorithm is determined by the following factors [8].

- Image Quality
- Compression ratio
- Computational complexity and Memory requirement
- Energy Consumption

2.1. Image quality

Compression is re-representation of the input data by reducing its original size. So there is always need for factor which defines amount of differences between the two entities, the original and the compressed data. Amount of change or the distortion exhibited in the compressed image is represented by image quality. Image Quality measurements can be subjective or objective. Subjective measures are based on human perception and experiences in reporting the image quality. Objective measures are mathematical measures. There are many metrics to determine the image quality. The MSE, PSNR are the easiest and universally used models to compute the image quality. The SSIM is yet another better model to compute image quality.

2.1.1. Mean square error

MSE is cumulative squared difference between the original and the compressed image.

$$MSE = \frac{1}{mn}\sum_{x=1}^{m}\sum_{y=1}^{n}\left[I(x,y) - I^{'}(x,y)\right]^2$$

Where I is the original image pixel matrix and I' is the reconstructed image pixel matrix. Higher the value of MSE means lower the image quality.

2.1.2. Peak signal to noise ratio

PSNR is defined as the degree of error relative to peak value of the image and the amount of distortion present in compressed image. PSNR is measured in decibels and higher the PSNR value higher the image quality (for 8-bit grey scale image peak pixel value is 255) [16].

$$PSNR = 10\log_{10}\frac{x_{peak}^2}{MSE}$$

2.1.3. Structural similarity index measure

SSIM index describes the amount of image degradation professed (perceived) by the compressed image in the aspect of its structural information. SSIM is based on human perceptual model whereas MSE and PSNR are absolute errors. It is an objective measure to calculate perceptual image quality [17].

$$SSIM(i,j) = \frac{2\mu_i\mu_j + K1}{\mu_i^2 + \mu_j^2 + K1}\,\frac{2\sigma_{ij} + \mathrm{K2}}{\sigma_i^2 + \sigma_j^2 + K2}$$

where μ_i and μ_j are the sample means of i, j and $\sigma_\mathbf{i}$, $\sigma_\mathbf{j}$ are the sample variances of i, j, and σ_{ij} is the sample cross-covariance between i and j. The K1 and K2 are the variables used to alleviate the effect of division with weak divisor and their default values are 0.01 and 0.03 respectively [18].

2.2. Compression ratio

It is the ratio of the compressed image size to the size of uncompressed image. CR is measured in bits per pixel (bpp). Higher the compression ratio means the better compression. There is always trade-off between compression ratio and the image quality.

$$Compression\ \ Ratio(CR) = \frac{uncompressed\ \ image\ \ size}{compressed\ \ image\ \ size}$$

2.3. Computational complexity

This parameter describes computational load involved and its associated time and space complexities in the compression process. Lossy compression techniques require more computations hence increases the system complexity in terms of memory, power and processing capability. On the other hand, lossy compression techniques are well suited for the bandwidth limited VSN. Hence lot of researchers are working on resource efficient lossy image compression techniques adaptable for VSN [19,20]. The focused objective of this paper is to identify and analyse the lossy image compression algorithms developed for VSN.

2.4. Energy consumption

Energy consumption is the key parameter of any Wireless Sensor Networks; this parameter decides the lifetime of the network. The camera node and the forwarding nodes will deplete more energy, causing energy holes. In addition, complex computations involved in the compression will consume more energy that will shorten the lifetime of the network. In order to increase the life

Please cite this article in press as: Suseela G, Asnath Victy Phamila Y. Energy efficient image coding techniques for low power sensor nodes: A review. Ain Shams Eng J (2018), https://doi.org/10.1016/j.asej.2017.10.004

time of network it is obligatory to adapt low power consumption energy efficient, energy aware and light weight compression techniques [8,21].

3. Classification of image compression techniques

Image compression algorithms are broadly classified into lossy and lossless technique as shown in Fig. 3. Loss less compression is suitable for applications where image degradation is not tolerable i.e., field of medical imaging. The images which are compressed using lossy techniques will not be reconstructed as exactly as the original image. It is suitable for applications where loss of redundant data is tolerable. Lossy compression techniques are further classified into transform based and non-transform based techniques. The raw input image is transformed in to a comfortable form so that machines can access and read easily. The spatial information present in the image is grouped in to a form based on the frequency of occurrence of pixel data. This approach is termed as transform based compression.

3.1. Role of transform

Image transforms will not alter or compress the information content rather they will cluster the information residing inside the image based on the set of basis function. The need of image transform is to make further operations on the image like image analysis, compression and segmentation, at an easy and convenient way. Out of all, transforms allow the system to do fast computation and manipulation. Popular transforms such as Fourier transform, DCT, DWT will group the information content based on their frequency of occurrence from time domain to frequency domain. Transforms allow the image analyst to extract more information, which might be used to predict significance of the information. After transformation, the critical components of the image data are isolated, which allows the image analyst to work directly on these components. Transforms are classified based on the type of basis function. They are orthogonal sinusoidal, non-sinusoidal, statistical and directional transforms. The popular transforms like Fourier transform, DCT are under the category of orthogonal sinusoidal transform and DWT is non-sinusoidal transform. Transform based image compression algorithms will follow the chained three step process - transformation, quantization and entropy encoding. The quantization may be scalar or vector. Finally, the quantized transformed coefficients are entropy coded [9].

3.2. Non-transform based compression

This category of image compression algorithms will not follow the three step chained process. Vector Quantization and Fractals are non-transform based compression. One such findings is realized by Lecuire et al. [21] who used 2×2 tiny block size image coding with pixel removal technique and Torus Automorphism for robust energy efficient image communication over Visual Sensor Network.

Non-transform-based algorithms include fractals and Vector Quantization (VQ). Mammeri et al. (2012) states that the main drawback of fractal image compression is related to the encoding process which is extremely computationally intensive and time consuming due to the hard tasks of finding all fractals during the partition step and the search for the best match of fractals. The limitation of VQ is its complexity, which increases with the increasing of vector dimension and it may decrease the coding speed and increase the power dissipation especially in power-constrained applications such as VSN. Another disadvantage of VQ is related to the design of a universal codebook for a large database of images, which requires a large memory and huge number of memory accesses.

Experiments done by Mascher et al. (2007) and from the survey done by Mammeri et al. (2012), it is found that transform based coding methods have relatively less energy dissipation than VQ and fractals [22]. In general, the design of an energy efficient transform based compression algorithm depends on all stages of the compression (Transform – Quantization – Coding) and the interconnection between those stages. The VSN is characterized and sternly affected by hardware limitations. The solution for energy efficiency can be achieved with hardware implementation or software implementation [12,23]. Kaddachi et al. (2011) proposed hardware solution for energy efficient compression for still images by implementing DCT in FPGA and reported that hardware based image compression are faster. Hasan et al. (2014) had done a survey on this subject [24].

3.3. Image compression algorithms based on discrete cosine transform

Before debating the DCT-based algorithms, the principle of DCT [25] is described concisely. The DCT is a transform technique for

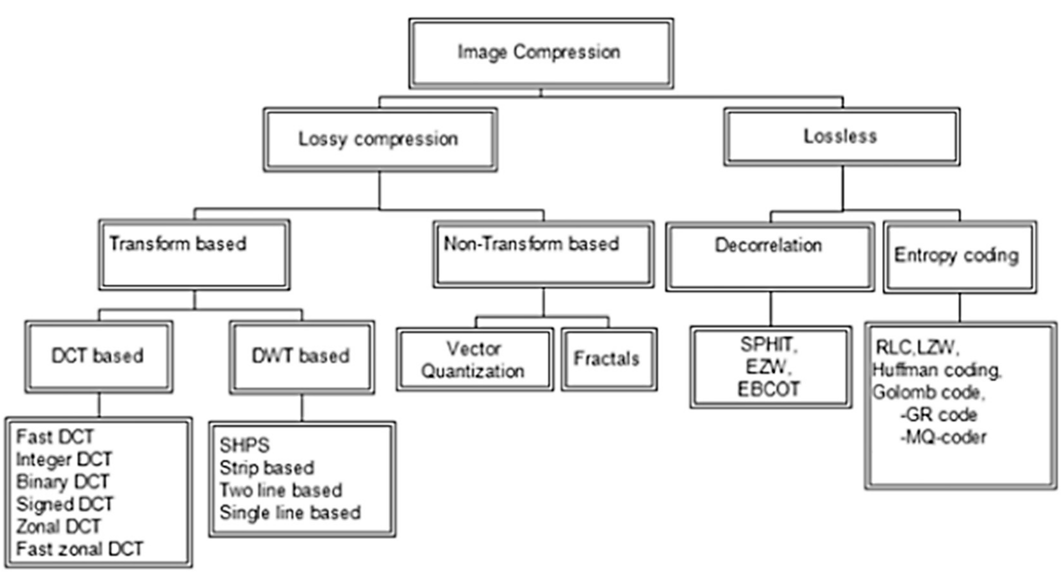

Fig. 3. Classification of image compression algorithms for resource limited platforms.

mapping a signal into essential frequency components. The DCT coefficients are real valued and they provide close approximations of the input data. There are four types of DCT. Out of them DCT-II is widely used and accepted for most image processing techniques. The first step is dividing the image into small blocks usually matrix of size 8×8, and for each tiny block, DCT is applied. Mathematically 1D-DCT is defined as the sum of cosine functions wavering at various frequencies. For a matrix 2D-DCT is obtained by serializing the two 1D DCTs, one by row wise and another by column wise. The traditional image compression standard JPEG is based on DCT [26]. Fig. 4. depicts the typical DCT-II inside the baseline JPEG compression standard.

3.3.1. Steps in JPEG compression

1. Discrete Cosine Transform of each 8×8 pixel matrix $f(x,y) \rightarrow_T F(u,v)$
2. The DCT output matrix is quantized with a quantization table or using a constant. The quantization done to reduce the number of coefficients. Thus, quantization introduces the loss.
3. Zig-Zag scanning is done to exploit redundancy. Conversion of 8×8 matrixes into 1×64 vectors. This scanning seizes the low frequency coefficients at the beginning of vector and high frequency coefficients at the bottom of the vector.
4. Differential Pulse Code Modulation (DPCM) applied on the DC component and Run length coding on the AC components.
5. Finally, the resulting vector encoded with lossless Huffman entropy coding.

Since DCT is the heart of the JPEG standard, its speed decides the efficacy of the JPEG standard. A pure DCT for 8×8 block requires 466 additions and 96 multiplications [27]. Even the fast DCT called as LLM DCT for the complete 8×8 2-D transform is computationally intensive, the LLM 1-D DCT must be performed once for each of the 16 rows and columns, leading to a total of 192 multiplications and 512 additions [28,29]. Because of more computations involved at transform stage, JPEG is not beneficial to VSN. Lot of works has been proposed in the literature to speed up the DCT by reducing number of computations involved. Lee et al. (2009) had contributed a platform based JPEG compression tool adaptable to VSN with acceptable image quality [30]. With respect to precision, the floating point DCTs are complex but the reconstructed image quality is good. Fixed-point implementations and integer DCT are less complex but introduces more distortion [31,32]. For a camera equipped VSN with light weight processor, DCT based compression algorithms are best adapted because of its low memory implementation (8 x 8 tiling style), good power compaction, and coding gain, all leading to good compression ratio. Many modified and improvised versions of DCT were reported in the literature in achieving low complex DCTs with reduced computations. All variants still holds the properties of pure DCT like orthogonal, separable, energy compaction, no DC leakage etc. The popular variants of DCT are itemized and described.

3.3.2. Fast DCT

DCT is computationally intensive and energy consuming. Chen et al. (1977) proposed a first version of fast DCT [33]. Then Loeffler et al. (1989) had found the fast DCT with 11 multiplications and 24 additions for computing 1D-8 point DCT [34]. They have used plane rotations. Iteratively only 32 cosine functions are involved in DCT, if they are precomputed once and used to calculate 8×8 output matrix that requires 128 Multiplications and 63 Additions. This precomputation technique is also one of the Fast DCTs [29]. The cosine values are real valued but not integer friendly. Most of the VSN hardware architectures are not built up with floating point processors. Hence, this is not feasible for VSN.

3.3.3. Integer DCT

The integer DCT (Int DCT) maps integers into integers and requires only lifting steps and additions. Thus, the integer DCT implementation is impressively simplified. Because of integer-to-integer, mapping this version of DCT allows lossless compression. In the literature, 8 point, 16 point and N (N is power of two) point fast integer DCT using Walsh-Hadamard transform along with lifting schemes [31,35,36] are referred. Though the integer DCT introduces rounding error, it is found that there is not much difference in PSNR when compared with floating point DCT [32]. Another version of integer DCT [37] is that the operations are not integer arithmetic but the output is aimed as integers.

3.3.4. Binary DCT

Fast multiplier less DCTs emerged out in the literature. The block-based Binary DCT is more VLSI friendly. This transform requires only adders and binary shifters. BinDCT proposed by Tran (2000) used lifting scheme to construct the multiplier less filter banks [38]. In order to replace the nonlinear computation of division operations by employing binary bit shift operation Tran et al. (2001) has chosen the lifting step to be dyadic [39,40]. To have integer-to-integer mapping, they have approximated the DCT's rotation angles by suitable dyadic lifting steps making BinDCT as a lossless transform. To compute the eight transform coefficients BinDCT uses only 13-bit shift and 30 additions. Because of the hardware friendly nature and reduced computations, many researchers have worked on Binary DCT [41].

3.3.5. Signed DCT (SDCT)

Tarek (2001) reported a novel DCT as a square wave transform (SWT) based on signum function and termed as Signed-DCT (SDCT) [42]. He applied signum function over the pure DCT. It is also multiplier less version of DCT but it is not orthogonal as it uses only

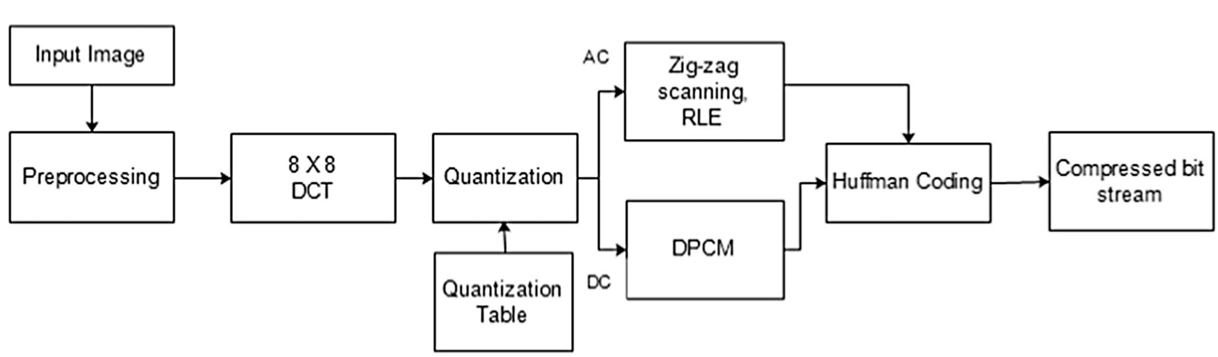

Fig. 4. JPEG Compression model.

adders for forward transform and requires shifters for inverse transform. Bouguezal et al. (2008) by fine tuning transform matrix of SDCT [43] addressed this issue. They have introduced zeros at appropriate positions of transform matrix for computations. This fast SDCT's performance is superior to SDCT and uses only 18 adders for both forward and reverse transforms.

3.3.6. Zonal DCT

Zonal DCT also known as pruned DCT is introduced by Wang [44,45]. The idea behind this technique is to reduce the complexity by omitting certain least significant DCT coefficients in an $n \times n$ block without losing noticeable image quality. The upper left corner of the DCT matrix contains most significant (low frequency) components because of energy compaction property. These low frequency components are retained of size $k \times k$ and the rest of the matrix are omitted where $k \ll n$. The choice of k decides the trade-off between computation cost and image quality. By reducing the DCT matrix, the chained three-step process (transformation, quantization and coding) will be profited with less processing time and computational cost. Thus, zonal or pruned DCT allows only k^2 computations instead of N^2. Mammeri et al. [46] have used this square shaped DCT coefficients in JPEG for VSN and named as S-JPEG and is depicted in Fig. 5.

3.3.7. Fast zonal DCT

The fast zonal DCT proposed by Vincent et al. (2012) preferred triangular shape of DCT coefficient matrix to the squared pattern to make it more convenient for VSN. They reduced the number of significant DCT coefficients from k^2 to $\frac{1}{2}k(k+1)$. The triangular selection of DCT coefficients is represented in Fig. 6. This is achieved by applying 1D DCT over all eight rows and only over the resulting k columns. This reduced block size DCT version is integrated in JPEG and termed as T-JPEG (Triangular JPEG) [47]. The investigators of [41] fused triangular zonal DCT and binary DCT. The experimental results confirmed energy savings and extended the lifetime of the image processing nodes in the VSN.

4. Image compression algorithms based on discrete wavelet transform

Discrete wavelet transform is a contemporary image processing technique to transform and analyse the image [48]. The wavelet transform decomposes and de-correlates the data in to multi resolution subbands i.e., permitting an image analyst to gouge out the significant components of the sample [49]. The subbands fostered tree based entropy coding to identify archetypical patterns like set

DC	10	7	1				
8	-2	3	4				
-4	1	0	-1				
3	1	0	3				

Fig. 5. Zonal DCT with k = 4.

DC	10	7	1				
8	-2	3					
-4	1						
3							

Fig. 6. Triangular zonal DCT with k = 4.

partitioning in hierarchical trees (SPHIT). The DWT has attained wide attention over DCT in image compression because of the following features [50],

(I) The transform is applied to the entire image, i.e., it uses non-block based approach and it does not suffer with block artifacts as in DCT.
(II) This transform retains both time (space) and frequency information of the original data. If detailed the wavelet transforms allow good frequency resolution for low frequency components and good temporal resolution for the high frequency components.

We have summarized the wavelet transform generalists without the need of sound knowledge in signal processing. This transform decomposes the input signal into approximation and details. The entire input image is first applied one dimensional filter along rows yielding two sub bands L and H, where L indicates Low pass band and H indicates High pass band. In the second step, these resultant bands are allowed one-dimensional filtering by column wise, generating the resultant bands as LL, LH, HL and HH. Fig. 7 shows the two level decomposition of 256×256, image by DWT. LL band holds the approximated, coarse, smoothen version of the original image, and represents the general trend of pixel values of the input image. LH (horizontal details) band clutches the row wise elements, HL (vertical details) band clutches the column wise elements and HH (diagonal details) contains the oblique elements of the original image. The wavelet coefficients of each band are depicted in Fig. 8. The image compression standard JPEG2000 is based on DWT. Zuo et al. (2012) have used JPEG2000 compression in bi-level hopped image transmission scheme to lengthen the network life time of their sensor nodes [51].

4.1. JPEG 2000

The lead role played by block based DCT in baseline JPEG had been replaced by DWT in JPEG2000 [27,52]. The block diagram of JPEG2000 is shown in Fig. 9. JPEG 2000 has long list of features for its wide acceptance. As far as VSN is considered the following features gained the researchers attention on it. The interesting features are low bit-rate compression performance and significance identification [53]. Table 2 gives a comparison of DCT and DWT

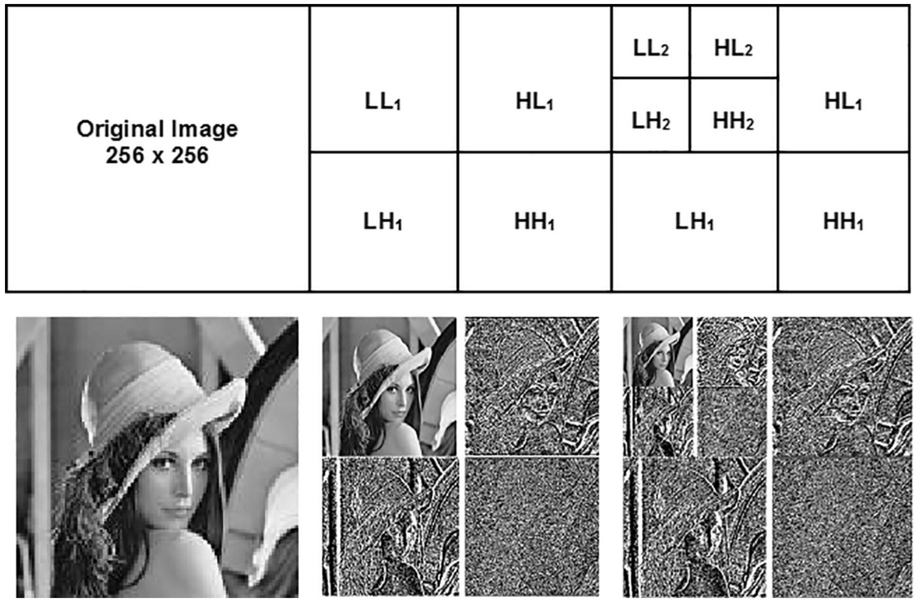

Fig. 7. Two level DWT decomposition.

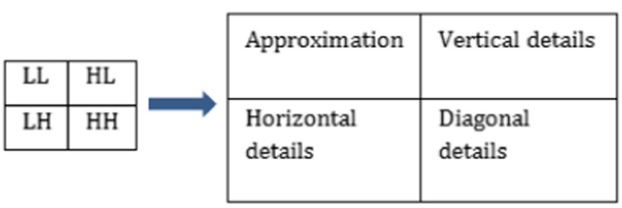

Fig. 8. DWT subbands and their contents.

with respect to resource limited VSN [8]. The computation complexity is high in DWT over DCT however, it offers good compression ratio and image quality at the higher cost of memory. Attention in low memory concerns in DWT has been found as one another challenge in wavelet based image compression. Therefore, the researchers are working on making the wavelet transforms adaptive to the resource-limited platforms.

The wavelet transform coefficients are entropy coded such as EZW, SPHIT, and EBCOT. Because of the very good energy compaction of DWT, numerous transform based compression algorithms use DWT as the mapper and tree based EZW, SPHIT as coders.

4.2. EZW (Embedded zero tree wavelet-based) image coding

The principle of embedded image coding is that the bit stream is transmitted in the order of their importance. Each received bit stream will increase the picture quality by reducing the distortion.

Table 2
Comparison of DCT and DWT.

	DCT	DWT
Memory requirement	Low	High
Computation Load	Low	High
Compression ratio	Low	High
Power consumption	Moderate	High
Localisation	Moderate	Very good
Processing speed	High	Low
Significance identification	Moderate	Very high
Image quality	Low	High
Edge correlation	Poor	Good
Complexity	Low	High

Embedded coding allows intrinsic progressive transmission. The encoding can be dismissed at any point of time with when the required image quality or bit rate is obtained. EZW encoder is introduced by Shapiro [54]. It is a wavelet transform based embedded coding. It works very well on natural images. The inherent progressive nature allows this compression suitable for VSN [55]. Since wavelets allow multi resolution analysis at multilevel decomposition, they can be coded in decreasing order. EZW scanning order is shown in Fig. 10.

The EZW involves two passes i.e. dominant pass and refinement pass. The dominant pass finds the self-similarity across the coefficients. In the first pass, the first value of the threshold value T is chosen and all the wavelet coefficients are compared with T. The transform coefficient is encoded as stated in [54]. When all the wavelet coefficients have been scanned, the threshold value is

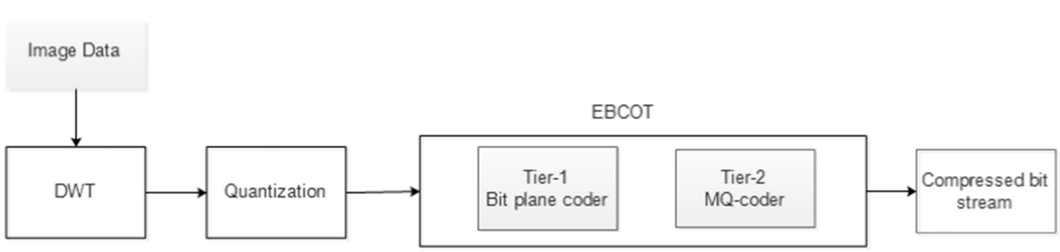

Fig. 9. JPEG 2000 compression.

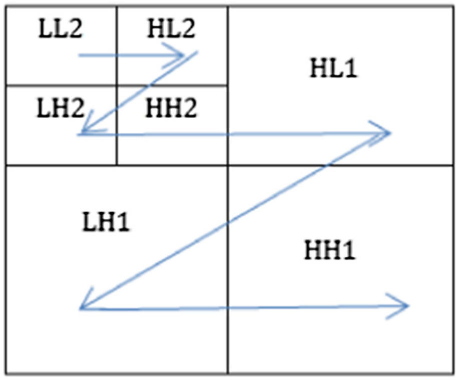

Fig. 10. Zero Tree Scanning order.

reduced by a factor of two. The scanning process is continued, to add more detail to the already encoded image, until the required bit rate is achieved. In refinement pass, the significant coefficients identified in dominant pass are quantized with successive approximation. However, the difficulty of EZW is that since more number of passes are required to achieve better compression, it consumes more energy and more space in VSN.

4.3. SPHIT (set-partitioning in hierarchical trees) image coding

Said and Pearlman first introduced SPHIT codec [56]. This coder is also similar to EZW based on identifying self- similarity patterns over the wavelet coefficients. It is an improvised version of EZW. The main difference of SPHIT coder from EZW is by the rules tree structure is partitioned and ordered. The wavelet coefficients are ordered into Spatial Orientation Tree. SPIHT comprises of three passes to generate three significant lists by comparing against chosen threshold value. The insignificant pixel pass produces LIP (list of insignificant pixels), insignificant set pass produces LIS (list of insignificant sets) and significant pixel pass produces LSP (list of significant pixels). The SPHIT coder is a powerful compression tool as it does not require source coder and hence increases the coder efficiency. The major drawback of SPHIT is that it requires more memory because of retaining the lists. It also requires more computational overhead in sorting. Many modified and improved storage competent versions of SPHIT are available in the recent literature [57–61]. In [58] the research is about implementation of MSPHIT with single list instead of three lists. The authors of [60,61] implemented listless approach of SPHIT.

4.4. Low memory DWT implementation

Usually DWT is applied to the whole image and n-levels of decomposition at multi resolution are stored to follow the three-step process of compression chain. This type of image transformation demanding the full image is not realistic in hardware-limited environment where only restricted storage is available.

4.4.1. Adaptive DWT for VSN

Nasri et al. had implemented image compression for VSN using DWT [62]. They aimed to reduce the data communicated over the network. The ideology is that the image is wavelet transformed. The low pass subbands LL and LH alone are computed and considered for communication as shown in Fig. 11. They have realized that high pass bands contain details less than 0.2% of the original image. So skipping these coefficients will not lead to much loss in image quality. The high pass subbands HH, HL are not computed and they have named this scheme as Skipped High Pass Sub-bands (SHPS). Since LL and LH are only computed, the computation load is reduced by 25% compared with CDF 9/7 and in second level of compression computational load is only 6% compared with the first level. Thus, SHPS approach offers 31% of energy gain and confirms increased network life-time of VS node.

4.4.2. Line based wavelet transform:

The image data is acquired by scanning serially one line at a time. Chrysafis and Ortega (2000) have applied line-by-line data acquiring method for their line based DWT implementation [63]. They found that 1D-DWT for a single line is done without the need for more memory, but columnar separation in 2D-required more memory. One-dimensional transform is performed and as the sufficient number of lines is processed, they are 2D transformed and then the memory is freed. Then for entropy encoding, line based low memory encoder with context modelling is used.

In low memory line based DWT, though the implementation reduced the memory requirement for transformation, it still required the whole DWT subbands for further SPHIT entropy coding. In [64] investigators adapted line based DWT as strip based which lead them to great improvements in terms of low memory requirement for SPHIT entropy coding. N lines of image is wavelet transformed and they are stored in the strip buffer for coding using SPHIT.SPHIT is done for these lines and transformation of next n-lines is done in parallel. This significantly reduced memory requirement of SPHIT. Further improvements are found in the literature to reduce the memory requirement of wavelet transform based compression scheme [65–68]. To fulfil the memory constraints in VSN Stephen et al. (2009) fetched two lines of pixel data for wavelet transformation which required coarsely 1.5 KB of RAM to compress a grey scale image of size 256×256. They attempted in offering high quality of picture with low complex Wavelet transform coding [65]. The Stephen et al. (2011) in another work fetched single line of pixel data for DWT and complemented the floating-point wavelet coefficients with fixed-point arithmetic [66]. The integer operation is best preferred in camera equipped VSN [67]. Lenning Ye et al. implemented a novel image-coding scheme called

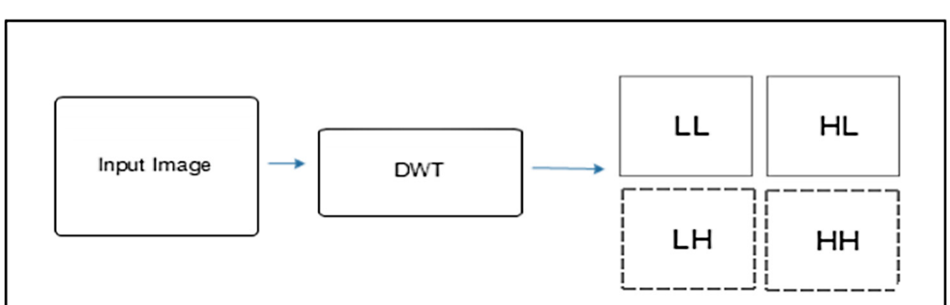

Fig. 11. SHPS-LL, HL are computed and LH, HH are skipped.

Please cite this article in press as: Suseela G, Asnath Victy Phamila Y. Energy efficient image coding techniques for low power sensor nodes: A review. Ain Shams Eng J (2018), https://doi.org/10.1016/j.asej.2017.10.004

BCWT (Backward Coding Wavelet Trees) using line based wavelet transform [69].

5. Lossless entropy coding techniques

The procedure of assigning binary digits to the transformed and quantised output is known as coding. It is essential in compression to have less average length of bits per pixel for the image. Instead of storing each character in a file as an 8-bit ASCII value, source coding replaces each input symbol with specific codeword. There are many techniques in the data compression literature such as Huffman coding, Run Length Coding, Variable Length Coding, Arithmetic coding, Golombs-Rice code and MQ-coders. Block Truncation Coding (BTC) is not an lossless coding, but it also has its own place in coding zone, it is also discussed.

5.1. Huffman coding

The Huffman coding is optimum prefix code. Prefix code is that no code word is the prefix of another code word. In an optimum code, the more frequently occurring symbols are coded using shorter code words and less frequently occurring symbols are coded using longer code words. The Huffman code requirement is that two symbols with lowest probability will have same length of code word and they differ only in least significant bit. Huffman coding is used in JPEG. However, Huffman code requires complete Huffman table in the compressed file for decoding and suffers with transmission errors, which is unavoidable in wireless networking.

5.2. Arithmetic coding

Instead of assigning each occurring symbol with specific code word, Arithmetic coding assigns a stream of input symbols with a single floating point number in [0,1) using interval subdividing procedure. It uses the probabilities of the source messages to contract the interval successively to represent the ensemble. Arithmetic coder yields better compression ratio since single value is coded for all symbols. The complexity of the coder is high and most of the VSN platforms are not equipped with floating point hardware.

5.3. Run length coding

Coding the lengths of runs instead of coding each symbol is the ideology behind run length coding. It is very much suitable for binary symbols. After zig -zag scanning of AC-coefficients run length coding is used in JPEG.

5.4. Dictionary based coder

Dictionary based coders are entropy coders that dynamically build the coding and decoding tables called dictionary, on the fly by observing at the data stream. These coders will not require the probabilities of occurrences of the symbols. LZW (Lempel-Ziv – Welch) coder is an example of dictionary coder. The encoder does not require probabilities of symbols in advance [70]. However requires more memory, which is not feasible in VSN. This is an open research issue yet to be solved.

5.5. Golomb - Rice code

Golomb code is based on assumption that larger value of an integer will have less probability of occurrences [71,72]. The simplest coding is unary representation of the symbols. A positive integer n for a parameter m is coded by two parts. Such that the first part is in unary- n div m, number of one's followed by one zero. The second part is coded with truncated binary coding- n mod m in binary with $\log_2$ (m) bits. When m is in powers of two, this coding technique terms to be Golomb-Rice code (GR code). GR code is based on the Low complexity and Low memory Entropy Coder proposed in [73] has been adopted by [41] and [74,75]. The chief elements in Low complexity and Low memory Entropy Coder (LLEC) are namely GR codes and ZTC (zerotree coding). ZTC exploits the zero tree structure of transformed coefficients for better compression adeptness. Usually Golomb -Rice coder and zero tree structure are suitable for image compression because of their less computational complexity over Huffman or arithmetic coding.

5.6. MQ–coder

The MQ coder is an approximate implementation of arithmetic coding developed for binary data. Application of Golomb and MQ coders as an alternative to Huffman or arithmetic coding significantly reduces the computational complexity and memory requirement [12]. As like arithmetic coding, encoding of symbols is proceeded by computing probability of symbols in the Golomb code. The initial interval is defined. The interval sub division is done with the probability of symbols. The MQ-coder is allowed to encode symbols in a fashion such that high probability symbols decrease the interval than low probability symbols leading to principle of optimum code. The MQ coders encodes stream of symbols as a number in range [0, 1].

5.7. BTC coding and its variants

Block Truncation coding (BTC) of image was first introduced by Delp and Mitchell [76].The image is divided into small blocks usually of dimension four by four**.** This coder preserves first and second order statistical moments of coded data and uses bi-level quantizer. It is a simple and fast coder and allows compression rate of 2 bpp (bits per pixel). The mean and variance are preserved and used to compute the quantizers. Each pixel data is compared against mean and set either zero or one. The encoder codes binary bit matrix along with 8-bit binary representation of sample mean and standard deviation. Thus, the grey levels are reduced and a 4×4 matrix is coded with as low as 32 bits achieving bitrate of 2 bpp. AMBTC (Absolute Moment BTC) is another member of BTC coding family, which codes high mean and low mean instead of mean and standard deviation [77]. The high mean is average of all pixel data in the block, which are higher than the mean. The low mean is average of all pixel data in the block, which are lower than the mean.

AMBTC has reduced distortion factor MSE over BTC. Lot of variants of BTC are suggested in the literature [78–84]. The bi-level quantization introduces more distortion. Somasundaram et al. have modified AMBTC by allocating 2 bits for each element in the bit plane with four level quantization for improved image quality [80]. Yang et al. have dealt the same issue using k-means algorithm to compute multi-level quantizers [81]. BTC has good compression but effect of block artifacting reduces the image quality with large block size like 16×16. Mathews et al. have addressed this issue in [82] and attained improved image quality. Their version of BTC is named as Modified BTC (MBTC) coder and uses max-min quantizer along with standard deviation. One another version of BTC is Max-Min BTC, which codes each pixel block using its maximum, minimum and average of maximum and minimum valued pixel data [83]. Enhanced BTC-EBTC reported in [84] reduces the bitrate from 2 bpp to 1.25 bpp.

Table 3
Energy consumption chart of various compression - techniques in the literature.

Work	Description	Processor	Image size	Energy consumption
Platform targeted JPEG, 2009 [30]	Floating point JPEG	ATmega128	128×128	2268.6 μJ
Platform targeted JPEG, 2009 [30]	SLOW JPEG	ATmega128	128×128	133.15 μJ
Platform targeted JPEG, 2009 [30]	FAST JPEG, Arai's DCT	ATmega 128	128×128	73.40 μJ
Platform targeted JPEG, 2009 [30]	Slow integer JPEG, LLM	ATmega128	128×128	105.50 μJ
Platform targeted JPEG, 2009 [30]	Fast integer JPEG, LLM	ATmega128	128×128	30.67 μJ
TiBS, 2011 [21]	Pixel mixing	ATmega128L	512×512	1612 mJ, Without quantization at radio transmit power 0 db
Adaptive image compression, 2011 [62]	SHPS	ATmega128L	512×512	0.6 Joules
Hardware based, 2012 [12]	CL-DCT in ASIC	ATmega128L	128×128	72.39 mJ
Two hop compression, 2011 [51]	Clustered approach And DCT	Strong ARM SA-1100	512×512	1 –level DWT 220 nJ/bit+ E_{code} 20 nJ/bit
Zonal DCT, 2012 [46]	Zonal CL-DCT k = 5	ATmega128L	128×128	417 μJ
Fast zonal binary DCT, 2013 [41]	Zonal DCT k = 2	ATmega128	512×512	7.30 μJ
Triangular DCT, 2010 [47]	LLM	MSP 430	128×128	33665 μJ
Triangular DCT, 2010 [47]	Triangular Zonal T = 4	MSP 430	128×128	27489 μJ
Triangular DCT, 2010 [47]	Triangular Zonal T = 2	MSP 430	128×128	19817 μJ
ABT, 2015 [68]	Line based DWT, LL band	ATmega128l	512×512	22.95 μJ
Low cost image sensor, 2015 [14]	Baseline –JPEG	Arduino MEGA 2560	128×128	1.251 J/s
Low power lossless image coding, 2015 [70]	LZW based coding	MSP430F149	320×240	756.36 mJ
Low power lossless image coding, 2015 [70]	modified RLE coding	MSP430F149	320×240	208.20 mJ

6. Energy consumption in the targeted resource constrained VSN

Energy efficiency in image communication can be obtained by reducing computations involved in the compression process and keeping the computational load less complex. It will extend the network life largely. Table 3 lists out the energy consumed by various compression schemes in the literature developed and adapted for VSN. All the DCT based algorithms presented in the table 3 shows energy required for an 8×8 block. The transceiver is the greedier power hunger component in the sensor nodes. The mica2 mote with chipcon1000 radio transceiver consumes 69 mW and 41 mW for transmission and reception respectfully. Therefore, to achieve energy efficient communication of pictures the compression algorithm should give more compression to have small size along with acceptable degradation in the image quality. The energy consumed by the compression algorithm in different stages is reduced by minimizing their computational cycles. In this finding, it is found that most of the implementations had been done with Mica and Telosb motes. The commercially available Mica2 mote is with Atmel ATmega 128 or Atmel ATmega 128L micro controller as its processors. The Telosb mote has MSP 430 as its processor. By analysing the data in Table 3, it is inferred that (1) the Atmel ATmega microcontrollers offer better energy savings than MSP 430 for both DCT based implementations and DWT based implementations. (2) Integer processing of DCT and DWT results in significant energy savings and (3) reduction in transform coefficients also introduced much energy gain by reduced data processing.

7. Conclusion

VSNs have emerged due to the contemporary advancements in Micro Electro Mechanical System (MEMS) Technology along with the fusion of various technologies with image sensors, embedded processing and computing. The problem of energy efficient image transmission with transform based and non-transform based compression scheme in multi hop wireless visual sensor network is investigated. Several categories of fast and complexity reduced DCT and DWT based compression schemes available in the literature are catalogued. Entropy coding techniques that are mostly prevalent in VSN are discussed with its merits and demerits. The inference from the analysis is energy consumption is purely dependent on implementation platform, algorithm complexity, implementation optimality etc. The energy consumption of different algorithms in various microcontrollers present in the VS node such as ATmega128, ATmega128l, MSP430, Strong ARM SA-1100, MSP430F149 and Arduino Mega are analysed. This survey provides substantial contributions to inquiries about image transforms and coding in Visual Sensor Networks. The conclusion arrived with respect to low power VSN platform is adapting transform based compression techniques with integer operations will be more appropriate for low power sensor nodes and for coding techniques low memory list or dictionary less techniques are appropriate. One such direction suggested is integer-based multiplier less hardware friendly fast zonal DCT along with dictionary less GR coding will offer energy efficient image compression with low computational load, high compression ratio and low memory usage with acceptable image quality. Fast zonal transform [41] consumes 7.30 μJ for processing an 8×8 block, which is only 0.3% of energy needed by true DCT and only 6% of energy needed by Independent JPEG Group (IJG-fast) version. Hope that this review paper will be compassionate valuable for future researchers who take up their research in image communication over low power environments.

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Please cite this article in press as: Suseela G, Asnath Victy Phamila Y. Energy efficient image coding techniques for low power sensor nodes: A review. Ain Shams Eng J (2018), https://doi.org/10.1016/j.asej.2017.10.004