Low Complexity Hardware Architectures for Wavelet Transforms: A Survey

Khamees Khalaf Hasan$^{1,2}$, Mahmood Ali A. Dham$^{1,2}$, Shahir Fleyeh Nawaf$^{1,2}$

$^1$Salahaddin Province, Tikrit, Iraq, P.O. Box (45)
$^2$Department of Electrical Engineering, Tikrit University, Salahaddin, Iraq
$^*$Corresponding author: kaljomaily@tu.edu.iq

Abstract. Presently, the major focus is on developing techniques to efficiently decrease hardware expenditure as well as hardware complications while realizing the requirements for a real-time system. The enhancement of Discrete Wavelet Transforms (DWT)’s hardware modelling is still a relatively novel subject of research. Such areas comprise developing an effective hardware acceleration of the implementation of the DWT of the JPEG2000 standard, to construct a practical model and to deal with the computational and communication energy limitations of the image compression system. This paper emphasizes a comprehensive survey to develop necessary solutions to enhance the potential and capacity of DWT’s computation-intensive nature algorithm implementation, particularly for low power image compression applications. The paper focuses on the major factors in order to lower the DWT principal energy consuming phase, given the energy consumption of the whole wavelet based image compression. These factors may possibly encompass some hardware-based features, such as basic coding features, low memory requirement, and low computational load. In combination with this research, other paper areas are also being investigated.

1. Introduction

Two years ago through 2015, it is documented that the volume of digital media transmitted to the regular end users in America will surpass 8.75 zettabytes yearly, or nine DVDs value of data daily. A zettabyte of information is equal to approximately 1,000,000 million gigabytes. These approximations are based on an evaluation of various sources of media information conveyed on mobile gadgets and to consumer homes, ranging from traditional media, like radio, TV, and mobile cell phone, to latest digital media resources, such as Internet programs, smartphones, notebooks, and computer gaming. Figure 1 depicts a few basic media content flows to conventional consumer devices [1]. Image and video usage comprise the bulk of bit transfer, leading to their significantly soaring rates of consumption, number of consumers, and task, in contrast to other information components. The disproportion between demand and supply continues to widen due to the tremendous increase in demand, in addition to transfer constraints, which has made compression facilitating technology a highly sought after utility in the information era [2]. The storage or transmission of digital data devoid of compression is not viable and can be disastrous. Therefore, creating a system that can solve the problem of high memory-storage in image processing is essential [3]. Data compression is recognized as a technique that transforms an input data into a more concise representation of the data with less volume of bits in contrast to the original input data so as to reduce data storage prerequisites and thus communication expenses [5].
Decreasing the data storage requirement is consistent with increasing the capacity of the storage medium and consequently communication bandwidth. Therefore, the need for effective compression methods will continue to be a design challenge for potential communication systems and advanced multimedia applications [5]. Image compression can be further developed as an effective transmission technique for eliminating superfluous information present in a digital image [4].

This paper comprises of six sections. Section one entails a synopsis of image compression techniques and their applications. Section two presents a review of the data compression techniques, the theories and principles. Section three includes a concise appraisal of theoretical approaches of the data compression setup used in the paper. Section four contain the General image compression schemes framework of the research. Section five involves comparison of performance of the wavelet architectures. Finally, Section six consists of the concluding part of the paper.

2. Data compression concept
Data comprises a combination of information and redundancy. Information is the part of data that needs to be stored permanently in its actual form to accurately deduce meaningful information from the data, while redundancy is the part that can be eliminated when it is not required or restored when necessary for improved data inference [4]. Data compression is the conventional method for removing the redundancy of data. Afterward, the redundancy can be later reinserted to restore the original data via decompression of the data [4]. The compression and decompression are occasionally regarded as the combination of coding and decoding techniques into a solitary system to create a CODEC structure. The reconstructed data could be similar to or an estimate of the original data, based on the reconstruction conditions. Figure 2 illustrates a basic diagram of a CODEC system [4].
A CODEC is referred to as a lossless technique if the reconstructed data is a precise reproduction with features similar to the original data. Conversely, the CODEC is a lossy technique when the reconstructed data is not accurately similar to original data [4]. In general, the expressions, noiseless or noisy coding, denote loseless and lossy compression techniques respectively. The term noise means the error of reconstruction in the lossy compression techniques since the reconstructed data item is not indistinguishable from the original one [4] [5].

3. Data Compression Modelling
Data compression can be applied to numerous kinds of media [4]. Image compression involves the use of data compression in digital images. The aim of image compression is to lessen of varying type’s redundancy of the image data in order to collect or transmit data in a well-organized form [4]. A model of a characteristic image compression system comprises three major components; deletion or decrease in source redundancy with the objective of reducing the duplicate information, reduction in entropy so as to dispose of extraneous information not perceived by the human visual system (HVS), and lastly, deploying an effective entropy encoding [4] [5]. Figure 3 illustrates a generalized block diagram of a data compression model.

![Figure 3. Compression and decompression CODEC](image)

A recognized feature of most images is the observable fact that adjacent pixels are typically spatially correlated; thus, detail contained in the neighboring pixels is redundant [4]. Three types of redundancy can be explored, and they include, spatial, spectral and temporal [5]. In still images, spatial redundancy is the most predominant due to patterning and self-similarity within the non-edge smooth area in the image [5]. Spectral redundancy integrates the different spectral bands or color planes. Temporal correlation has been extensively used in video compression of successive frames [6]. Currently, transform-based coding methods have drawn lots of attention because of its ability to decorrelate image data by eliminating spatial and spectral redundancies in still images [6]. The widely accepted techniques used in the redundancy reduction procedure include Fourier- related transforms such as Discrete Cosine Transform (DCT), disintegration of the original data set into various subbands such as Discrete Wavelet Transform (DWT), and so on. In principle, these techniques have the possibility of generating more compact representation of the pixel information of the original data set. For loseless data compression, this step is entirely reversible [6].

The next step involves lowering the entropy of the transformed data considerably so as to assign smaller bits for transmission or storage. The decrease in entropy is realized by removing lesser comparative significant information in the transformed data depending on the application measures [7]. Visual and auditory perceptions are fairly restricted to a specific frequency spectrum. For example, the eye demonstrates different levels of sensitivity to visual information. Redundancy enclosed in an image exceeding the human sensorial frequency threshold will be entirely invisible to
the human senses and is undetectable by the eyes in standard visual processing [7]. For this reason, it is not apparent and can be removed without visually affecting the quality of the picture. Given that the involvement of human perception in quality analysis of reconstructed data does not entail quantitative analysis of each pixel in the image, additional reduction of redundant data can be achieved [7]. This step is applied in lossy data compression schemes and this is generally achieved with some type of quantization technique. This is an irreversible process because it is not feasible to precisely extract the lost data or information using the inverse process. The character and quantity of quantization determine the quality of the reconstructed data [7].

The quantization procedure is subsequently followed by lossless encoding using a number of entropy schemes to efficiently characterize the quantized data for storage or transmission. Given that the entropy of the quantized data is relatively lesser than the original set, it can be denoted by fewer bits, thus compression is achieved and can be regarded as a technique for lossy image compression [4]. The decompression system is just an inverse procedure. Firstly, the compressed image is decoded to produce the quantized coefficients. Afterwards, the inverse quantization step is applied on these quantized coefficients to generate an estimate of the transformed coefficients. The quantized transformed coefficients are then inversely modified to create an approximate adaptation of the original data. The absence of quantization and inverse quantization steps in the CODEC system and the use reversible redundancy removal produces the precise reproduction of the original data and therefore the compression system can be referred to as a lossless compression system [4] [5].

4. General image compression schemes framework
Concisely, image compression is a technique used to represent an image with fewer numbers of bits with no damage to the visual and information quality of the image itself. The reduction of redundancy can be minute or huge depending on the type of compression technique. The amount of redundancy eliminated using lossy compression is greater than that of lossless compression. Figure 4 illustrates a generalized image compression framework. Quantization is a component of the supplementary preprocessing block in the image compression framework. This step should be skipped if loss of information on media could bring about unwanted results. Therefore, the most suitable compression technique should be applied based on the application and the final user to explore the compressed file [4].

![Figure 4. General image compression framework](image)

Lossless image compression techniques are often selected for high value data, for example medical imagery or image scans developed for archival purposes. However, if a vital image such as a digital mammography requires compression, it is apparent that lossless compression must be employed while quantization has to be avoided, since lossy compression methods introduce compression
artifacts, particularly when utilized at low bit rates. An incorrect diagnostic accuracy analysis of these images types could be catastrophic for patient undergoing physical evaluation [4].

For cases when the information depicted in an image is not significant, further compression of the image can be performed using lossy compression techniques. Further quantizing and decreasing the amount of bits representing the image will lead to perceptual data loss and promote effective storage and transmission potential [7]. Lossy methods are particularly appropriate for natural images such as pictures in applications where negligible data loss is allowable to attain a considerable decline in bit rate.

The most generally used image coding and decoding CODEC standard in recent times is the Joint Photographic Experts Group (JPEG), which utilizes discrete cosine transform (DCT) kernel. DCT-based algorithms are rapid with low complication and low storage capacity applied to equal 8-by-8 blocks of raw image data. Nonetheless, JPEG has several restrictions, particularly at low bit-rate applications [8]. For every pixel contained in a single block, two-dimensional (2D) DCT and entropy coding are applied discretely to utilize the correlation within the block. Spatial correlation from DCT adjoining blocks is disregarded, which frequently results in blocking artifacts and subsequently have an effect on the effectiveness of the coding system. An interpreter may not accurately identify the reconstructed image because of the degradation of image quality [9]. Thus, it is requisite to remove all limitations and affix novel improved features.

Wavelet transform functions efficiently on Multi-resolution analysis (MRA), which has been established as a versatile and highly effective technique for sub-band decomposition of signals [10]. MRA has been shown to be consistent with the low level characteristic of human vision to achieve enhanced biased lossy image compression results [11]. MRA algorithms developed with the DWT deals with the limitations of the Fourier transform and its derivatives [10]. Wavelets surpass other more conventional decomposition techniques such as the DFT and DCT with basis functions more appropriate for denoting images. This is due to its ability to represent information at various levels, with local contrast changes, in addition to larger scale structures and thus is a better fit for image data. The basis functions related to wavelet decomposition usually have long support for efficiently represent slow variations in an image and short support for efficiently represent sharp transitions i.e., edges. The DFT and DCT basis functions have support over the entire image, making it hard to represent both slow variations and edges efficiently [11].

Wavelet transforms have been confirmed to be exceptionally successful for transform-based image compression, where it substitutes the DCT in new JPEG2000 and MPEG4 image and video compression standards [11]. Given that several of the wavelet transform coefficients for a typical image are likely to be very small or zero, these coefficients can be coded without difficulty. Hence, wavelet transforms are a valuable tool for image compression [11].

Wavelet-based image compression comprises two stages: the wavelet transforms and the coding or compressing of the transformed components to take into consideration the data compaction technique [12]. A number of algorithms have been recommended to compress wavelet-transformed coefficients as much as possible, and they include Embedded Zerotree Wavelet (EZW) [13], Set Partitioning in Hierarchical Trees (SPIHT) [14], and Embedded Block Coding with Optimized Truncation (EBCOT) [15]. EBCOT was adopted by the popular still image compression standard JPEG2000 [16].

The 2D-DWT is considered the main resource-intensive component of JPEG2000 because it requires substantial computations and represents one of the significant areas in the development and performance of the JPEG2000 standard [19]. 2D-DWT is a major operation and is recognized as the principal phase in energy consumption of the whole wavelet-based image compression process. Optimum algorithmic features included in the wavelet transform step will contribute noticeable improvements to the overall performance and energy requirements of the whole compression system [12]. Consequently, instead of studying the whole DWT-based image compression process, this paper focuses on DWT stage to decrease energy consumption since it consumes 40% to 60% of the CPU time all through the compression procedure with the use of JPEG2000 [12].

DWT has been executed with the conventional convolution method, which involves filtering and sub-sampling of the input image to generate multi-scale image decomposition [10]. In recent
times, lifting scheme (LS), a mathematical representation of the wavelet transformation, has been applied as a trivial computation technique for performing wavelet transforms using the spatial approach [17]. With the use of filter factoring algorithm, the conventional DWT finite impulse response (FIR) filter bank is fragmented into a sequence of smaller lifting step filters [18]. The factored polyphase analysis fragment the FIR filter bank into a succession of upper and lower triangular matrices and transforms the filter implementation into banded matrix multiplication [17].

The intricacies associated with the traditional convolution and LSs are evaluated based on the fundamental components required for implementation. LS is a very flexible system, with simple adders and shifters substituting multipliers. Consequently, it basically decreases the amount of multiplication and accumulation entailed in analyzing a DWT using a convolution approach [17]. The basis of the LS practically involves dividing the input signal into odd and even polyphase indexed components. This step is subsequently followed by a process that utilizes interchanging predicting and updating in-place steps by altering the set of samples to be analyzed in the next step [18].

The LS high algorithmic DWT performance in image compression validates its application as the essential part of the JPEG2000 standard. The Daubechies 9/7 and LeGall 5/3 LS DWT filters are used as the default JPEG2000 standard filters for lossy and lossless image compression respectively [16]. Since the JPEG2000 image coding standard was endorsed in 2002, cost efficiency and real-time limitations continue to be the major obstacles to hardware realization of JPEG2000 standard into consumer products [19]. These algorithms have very complicated hardware prerequisites and expend high amount of energy when processing data because of demanding intensive computational complexity. The implementation of complex algorithms is so computationally challenging that specific function hardware solutions is required to be developed [21].

Presently, an extensive array of processors, such as application-specific integrated circuits (ASICs) and Field-programmable gate arrays FPGAs are employed as hardware platforms to analyze intricate and demanding applications [22]. These processors are flexible and pose a prospective platform for device portability and real-time applications, and the option of devising fast computing systems [22].

ASICs are effective in areas of performance and power consumption, but require versatility since they contain no programmable resources. FPGAs and ASICs are both capable of implementing application-specific circuits, although FPGA circuits are reprogrammable via a configuration that details the logical functionality and connectivity [22]. The development of sophisticated and high-speed reconfigurable hardware in the form of FPGAs generates an enormous interest in real-time image processing to enhance the performance of a conventional hardware versatile and reusable solution [21]. Therefore, focusing on physical FPGA devices is essential to devising highly efficient systems at low cost rates using the hardware description language (HDL) [21].

To recognizes the prerequisites of the VHDL design. The VHDL code is created to meet the specifications and then simulated to achieve the appropriate functionality. Any further alteration to the code requires its repair, and subsequently simulated. This method carries on till the needed functionality is attained. The code is synthesized after it becomes is valuable using Computer Aided Design CAD tools, which possibly gives precedence to style constraints such as speed, space and power. Synthesis is an automated method of transforming a higher level abstraction, such as DWT behavioural description to a lower level abstraction, like a gate level netlist. Subsequent to the design synthesis after the time restraints are achieved, the design is set up for next stage, i.e., (PAR) Place and Route. PAR is frequently drawn as the preferred method of mapping a synthesized netlist based on place (physical location) and route (the interconnection of the equivalent blocks) [23]. The exact timing constraints of the design are derived and also the dimension of the design is regularly precisely calculated, consequently in the existence of ineffective constraints, the design must be changed from the beginning [37], [38].

5. Comparison of Performance of the Wavelet architectures

However, only a few studies on low power architectures are reported in the literature for computing the wavelet coefficients. Related studies on for 1D DWT processor were reviewed in this subsection. A synopsis of the hardware and timing demands of the various (9, 7) filter
implementations of the JPEG2000 standard for data size $N$ is outlined in Table 1. The hardware intricacy has been evaluated in relation to the data pathway. The memory size and organization needed to support multiple levels of decomposition has not been outlined in majority of the architectures, and thus excluded here [39], [40]. An approximation of the controller complexity has also been incorporated. The timing performance has been measured with regard to two parameters: the number of clock cycles required to calculate $L$ levels of decomposition and the clock period (i.e., the delay in the critical path).

**Table 1.** Hardware and timing comparison of the 1D DWT architectures for the (9, 7) filter computation on an input size $N$ with $L$ levels of decomposition

| Architecture | Data-path | Timing Requirements | Control complexity |
|--------------|-----------|---------------------|--------------------|
| Direct mapped [25] | 4 mult, 2 scaling adders, 8 registers, 6 delay units | $4+2N(1-1/2^L)+2T_m+2T_a$ | Simple |
| Folded [26] | 4 mult, 2 scaling adders, 8 registers, 6 delay units | $4+2N(1-1/2^L)+2T_m+2T_a$ | Moderate |
| MAC [27] | 4 MAC, 2 scaling registers | $4+2N(1-1/2^L)+T_m+2T_a$ | Moderate |
| Flipping [28] | 4 mult, 2 scaling adders, 8 registers, 6 shifter | $5+2N(1-1/2^L)+12+2N(1-1/2^L)+T_m$ | Moderate |
| Generalized [24] | 4 processors (each one with 1 mult, 2 adder, 2 register), 2 scaling mult | $4+L+2^L$ | Complex |
| Recursive [29] | 4 mult, 2 scaling adders, 7 registers, 3 delay unit, 6 mux | $N+L+2^L+4T_m+8T_a$ | Complex |
| DSA [30] | 2 processors (each one with 4 mult, 4 adder, 7 register), 2 scaling mult, 3 delay unit | $N+L$ | Moderate |
| DSP [31] | 2 MACs, each one with 2 mult, 2 adders, 12 register, output buffer, Round, Sub units, 2 scaling mult, prog. delay | $N(1-1/2^L)+2K+T_m+2T_a+T_{rd}+T_{sub}+T_{buffer}$ | Complex |

### 6. Conclusions

Based on hardware complexity, the earlier reported folded architecture [26] is the most straightforward and the DSP-based architecture in [31] is the most complicated. The remaining architectures display similar hardware complexity and mainly vary in the amount of registers and multiplexor circuitry. The control complexity of the architecture in [25] is very simple. On the contrary, the number of switches, multiplexors and control signals used in the architectures of [30, 31] are fairly large. The control complexity of the remaining architectures is reasonable. In terms of timing performance, the current architectures [25, 26, 27, 28 and 24] are all pipelined, with some [28, 24] exhibiting the highest throughput. Some architecture has fewer cycles given that it is RPA based, but its clock period is higher [29]. Lastly, architectures compute all the outputs of one level before beginning computations of the succeeding level, although there is an exception [29], which implements an RPA based approach and combines the computations of the higher levels with those of the first level. So it is possible that the memory prerequisites of this exemption [29] would be
subordinate to the others. Lifting Scheme for 2D DWT processor in [32, 33, 35, and 36] and Haar type in [34] are complex.

7. Acknowledgments
The authors would like to gratefully acknowledge Tikrit University, Engineering college for their support to work on this paper.

8. References
[1] James E. Short, (2013). “How Much Media? 2013 Report on American Consumers,” produced by the Institute for Communications Technology Management (CTM) at the USC Marshall School of Business, University of Southern California. October 2013
[2] W. Russell Neuman, Yong J. Park, Elliot Panek, (2012). “Tracking the Flow of Information into the Home: An Empirical Assessment of the Digital Revolution in the United States, 1960–2005,” International Journal of Communication, 6, (2012), 1022–1041.
[3] Tao, M., M. Hempel, et al., (2013). "A Survey of Energy-Efficient Compression and Communication Techniques for Multimedia in Resource Constrained Systems." Communications Surveys & Tutorials, IEEE, 15, No.3, PP. 963-972.
[4] Salomon, D. (2004). Data compression: the complete reference. Springer.
[5] Acharya, T., & Tsai, P. S. (2005). JPEG2000 standard for image compression: concepts, algorithms and VLSI architectures. (John Wiley & Sons).
[6] Mamun, M., Jia, X., & Ryan, M. J. (2014). Nonlinear Elastic Model for Flexible Prediction of Remotely Sensed Multitemporal Images. IEEE geoscience and remote sensing letters, 11, (5), 1005-1009.
[7] Rafael C. onzalez, Richard E. Woods, Steven L. Eddins. Digital Image Processing Using MATLAB. CA : (Pearson Education, 2007).
[8] Quijas, J., & Fuentes, O. (2014, April). Removing JPEG blocking artifacts using machine learning. In Image Analysis and Interpretation (SSIAI), 2014 IEEE Southwest Symposium on (pp. 77-80). IEEE.
[9] Luo, Y., & Ward, R. K. (2003). Removing the blocking artifacts of block-based DCT compressed images. Image Processing, IEEE Transactions on, 12, (7), 838-842.S
[10] Mallat, S. G. (1989). A theory for multiresolution signal decomposition: the wavelet representation. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 11, (7), 674-693.
[11] ADAMS, M. D. (2013). Multiresolution signal and geometry processing. filter banks, wavelets, and subdivision (Version: 2013-09-26) Adams, Adams. Victoria, BC, University of Victoria.
[12] Lee, D. G., & Dey, S. (2002). Adaptive and energy efficient wavelet image compression for mobile multimedia data services. In Communications, 2002. ICC 2002. IEEE International Conference on, 4, pp. 2484-2490. IEEE.
[13] J. M. Shapiro, “Embedded image coding using zerotrees of wavelets coefficients,” IEEE Trans. Signal Processing, vol. 41, pp. 3445-3462, 1993.
[14] A. Said and W. A. Pearlman, “A new fast and efficient image codec based on set partitioning in hierarchical trees,” IEEE Trans. Circuits Syst. Video Technol. 6, pp. 243-250, 1996.
[15] D. Taubman, “High performance scalable image compression with EBCOT,” IEEE Trans. Image Process., 9, pp. 1158-1170, 2000.
[16] D. Taubman, and M. Marcellin, (November 2001) JPEG2000: Image compression fundamentals, standards and practice, Boston, Kluwer Academic Publishers.
[17] W. Sweldens, “The Lifting Scheme: A Custom-DesignConstruction of Biorthogonal Wavelets,” Applied andComputational Harmonic Analysis, 3, No. 15, pp.186- 200, 1996.
[18] I. Daubechies and W. Sweldens, “Factoring wavelet transforms intolifting schemes,” J. Fourier Anal. Appl., 4, pp. 247–269, 1998.
[19] Mansouri, A., Ahaitouf, A., & Abdi, F. (2009). An efficient VLSI architecture and FPGA implementation of high-speed and low power 2-D DWT for (9, 7) wavelet filter. IJCSNS International Journal of Computer Science and Network Security, 9, (3), 50-60.
[20] Zervas, N. D., Anagnostopoulos, G. P., Spiliotopoulos, V., Andreopoulos, Y., & Goutis, C. E. (2001). Evaluation of design alternatives for the 2-D-discrete wavelet transform. Circuits and Systems for Video Technology, IEEE Transactions on, 11, (12), 1246-1262.

[21] Benkrid, K., Crookes, D., & Benkrid, A. (2002). Towards a general framework for FPGA based image processing using hardware skeletons. Parallel Computing, 28, (7), 1141-1154.

[22] R. Tessier and W. Burleson, Reconfigurable Computing for Digital Signal Processing: A Survey,” J. VLSI Signal Process. Syst., 28, pp. 7/27, May 2001.

[23] Ahsan, M. R., Ibrahimy, M. I., & Khalifa, O. O. (2011, July). VHDL Modelling of Fixed-point DWT for the Purpose of EMG Signal Denoising. In Computational Intelligence, Communication Systems and Networks (CICSyN), 2011 Third International Conference on (pp. 236-241). IEEE.

[24] Andra, K., Chakrabarti, C., & Acharya, T. (2002). AVLSI architecture for lifting-based forward and inverse wavelet transform. Signal Processing, IEEE Transactions on, 50, (4), 966-977.

[25] C.C. Liu, Y.H. Shiau, and J.M. Jou, “Design and Implementation of a Progressive Image Coding Chip Based on the Lifted Wavelet Transform,” in Proc. of the 11th VLSI Design/CAD Symposium, Taiwan, 2000.

[26] C.J Lian, K.F. Chen, H.H. Chen, and L.G. Chen, “Lifting Based Discrete Wavelet Transform Architecture for JPEG2000,” in IEEE International Symposium on Circuits and Systems, Sydney, Australia, 2001, pp. 445–448.

[27] Peng, and C.Y. Lee, “A Line-Based, Memory Efficient and Programmable Architecture for 2D DWT Using Lifting Scheme,” in IEEE International Symposium on Circuits and Systems, Sydney, Australia, 2001, pp. 330–333.

[28] Huang, C. T., Tseng, P. C., & Chen, L. G. (2002). Flipping structure: an efficient VLSI architecture for lifting-based discrete wavelet transform. In Circuits and Systems, 2002. APCCAS’02. 2002 Asia-Pacific Conference on, 1, pp. 383-388. IEEE.

[29] H. Liao, M.K. Mandal, and B.F. Cockburn, “Novel Architectures for Lifting- Based Discrete Wavelet Transform,” in Electronics Letters, 38, no. 18, 2002, pp. 1010-1012.

[30] H. Liao, M.K. Mandal, and B.F. Cockburn, “Efficient Architectures for 1-D and 2-D Lifting-Based Wavelet Transform,” IEEE Transactions on Signal Processing, 52, no. 5, 2004, pp. 1315–1326.

[31] M. Martina, G. Masera, G. Piccinini, and M. Zamboni, “Novel JPEG 2000 Compliant DWT and IWT VLSI Implementations,” Journal of VLSI Signal Processing, 34, 2003, pp. 137–153.

[32] C.C. Xiong, J Tian, J Liu. Efficient architectures for two-dimensional discrete wavelet transform using lifting scheme. IEEE Trans. Image Process. 2007; 16, (3): 607-614.

[33] C Cheng, K Parhi, High-speed VLSI implementation of 2-D discrete wavelet transform. IEEE Trans. Signal Process. 2008; 56, (1): 393-403.

[34] ALTERMANN, João; COSTA, Eduardo; ALMEIDA, Sérgio. High performance Haar Wavelet transform architecture. In: Circuit Theory and Design (ECCTD), 2011 20th European Conference on. IEEE, 2011. 596–599.

[35] Y Hu, and C C Jong “A Memory-Efficient HighThroughput Architecture for Lifting-Based Multi-Level 2-D DWT” IEEE Transactions on signal processing, 61, no. 20, October 15 2013.

[36] MEKONNEN, Tenager, et al. Energy Consumption Analysis of High Quality Multi-Tier Wireless Multimedia Sensor Network. IEEE Access, 2017, 5: 15848-15858.

[37] Hasan, K. K., Ngah, U. K., & Salleh, M. F. M. (2013, November). Multilevel decomposition Discrete Wavelet Transform for hardware image compression architectures applications. In Control System, Computing and Engineering (ICCSCE), 2013 IEEE International Conference on (pp. 315-320). IEEE.

[38] Hasan, K. K., Ngah, U. K., & Salleh, M. F. M. (2013, November). Low complexity image compression architecture based on lifting wavelet transform and embedded hierarchical structures. In Control System, Computing and Engineering (ICCSCE), 2013 IEEE International Conference on (pp. 305-309). IEEE.

[39] Hasan, K. K., Ngah, U. K., & Salleh, M. (2014). Hierarchical hardware architecture of discrete wavelet transform for image compression. Int. J. Comput. Sci. Inf. Technol. Res, 2, (4), 232-241.

[40] Hasan, K. K., & Abdul–Amir, S. O. (2009). DCT/DPCM Hybrid Coding For Interlaced Image Compression. Tikrit Journal of Engineering Sciences, 16, (1), 121-132.