iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 4 **Issue:** VIII **Month of publication:** August 2016

DOI:

Volume 4 Issue VIII, August 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

PEB Based DWT with an Efficient Fixed Booth Multiplier

Surya. P. P[1], Navin. Y[2]
[1]M.E. VLSI Design, JCT College of Engineering & Technology, Pichanur, Coimbatore
[2]Assistant professor, Department of ECE, JCT College of Engineering & Technology, Pichanur, Coimbatore

Abstract: Discrete Wavelet Transform (DWT) derived features used for digital image texture analysis. Wavelets appear to be a suitable tool for this task, because they allow analysis of images at various levels of resolution .The discrete wavelet transform is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. Since the proposed error compensation bias is realizable, the constructing low-error fixed width booth multiplier is area time efficient for VLSI implementation. Fixed width multiplier generates an output with the same width as the input. They are widely used in digital signal processing systems. The computation error is introduced if the least significant (LS) half part is directly truncated. To reduce the computation error, many compensation techniques were presented for array multipliers. There is an apparently trade-off between accuracy and hardware complexity. Recently, compensation works have been increasing focused on reducing the truncation error on the booth multiplier. In presented statistical and linear regression analysis to reduce the hardware complexity. However, the truncation error was partly depressed because the estimation information that came from the truncated part is limited. This study proposes a probabilistic estimation bias (PEB) method for reducing the truncation error in a fixed width booth multiplier. The PEB formula is derived from the probabilistic catalysis in the partial product array after the booth encoder. In addition, the low-error and area-efficient PEB circuit is obtained based on the simple and systematic procedure. In this way, the time-consuming exhaustion simulation and the heuristic process of the compensation circuit can be avoided. Furthermore, the hardware efficiency and low error are validated through our simulation results. The main advantage of this method has provided smaller area and smaller truncation errors.
Keywords— DWT, Estimation theory, Fixed-width Booth multiplier, Probabilistic analysis

I. INTRODUCTION

Wavelet transforms have become one of the most important and powerful tool of signal representation. Nowadays, it has been used in image processing, data compression, and signal processing. Wavelets allow complex information such as music, speech, images and patterns to be decomposed into elementary forms at different positions and scales and subsequently reconstructed with high precision. Signal transmission is based on transmission of a series of numbers. The proposed features have been tasted on images from standard Brodatz catalogue. The discrete wavelet transform is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. It is a tool separates data into different frequency components, and then studies each component with resolution matched to its scale. The main feature of DWT is multi scale representation of function. By using the wavelet, given function can be analyzed at various levels of resolution. The DWT is also invertible and can be orthogonal. Wavelets seen to be effective for analysis of textures recorder with different resolution. It is very important problem in NMR imaging, because high resolution images require long time of acquisition. There is an expectation that the proposed approach will provide a tool for fast, low resolution NMR medical diagnostic Booth Multiplier is a new methodology for designing a lower-error and area-time efficient 2’s complement, which receives two n-bit numbers and produces an n-bit product.

By properly choosing the generalized index and binary thresholding, we derive a better error compensation bias to reduce the truncation error. Since the proposed error compensation bias is realizable, the constructing low-error fixed width booth multiplier is area time efficient for VLSI implementation. The simulation results show that the performance is superior to that using the direct truncation fixed width booth multiplier. Fixed width multiplier generates an output with the same width as the input. They are widely used in digital signal processing systems. The computation error is introduced if the least significant (LS) half part is directly truncated.

Volume 4 Issue VIII, August 2016
ISSN: 2321-9653

To reduce the computation error, many compensation techniques were presented for array multipliers. There is an apparently trade off between accuracy and hardware complexity. Recently, compensation works have been increasing focused on reducing the truncation error on the booth multiplier. In presented statistical and linear regression analysis to reduce the hardware complexity. However, the truncation error was partly depressed because the estimation information that came from the truncated part is limited.

We propose a probabilistic estimation bias (PEB) method for reducing the truncation error in a fixed width booth multiplier. In addition, the low-error and area-efficient PEB circuit is obtained based on the simple and systematic procedure. The main advantage of this method has provided smaller area and smaller truncation errors. Furthermore, the hardware efficiency and low error are validated through our simulation results. The PEB formula is derived from the probabilistic catalysis in the partial product array after the booth encoder.

II. EXISTING SYSTEM

The Discrete Wavelet Transform (DWT) is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. In this normal Fourier transform is performed as it captures both frequency and location information (location in time). Discrete Wavelet Transform (DWT) derived features used for digital image texture analysis. Wavelets appear to be a suitable tool for this task, because they allow analysis of images at various levels of resolution. The proposed features have been tasted on images from standard Brodatz catalogue. The discrete wavelet transform is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. It is a tool separates data into different frequency components, and then studies each component with resolution matched to its scale. The main feature of DWT is multi scale representation of function. By using the wavelet, given function can be analyzed at various levels of resolution. Signal transmission is based on transmission of a series of numbers. The series representation of a function is important in all types of signal transmission. The wavelet representation of a function is a new technique. Wavelet transform of a function is the improved version of Fourier transform. Fourier transform is a powerful tool for analysing the components of a stationary signal. But it is failed for analysing the non-stationary signal where as wavelet transform allows the components of a non-stationary signal to be analysed.

Transform coding constitutes an integral component of contemporary image/video processing applications. Transform coding relies on the premise that pixels in an image exhibit a certain level of correlation with their neighbouring pixels. Similarly in a video transmission system, adjacent pixels in consecutive frames show very high correlation. Consequently, these correlations can be exploited to predict the value of a pixel from its respective neighbours. A transformation is, therefore, defined to map this spatial (correlated) data into transformed (uncorrelated) coefficients. Clearly, the transformation should utilize the fact that the information content of an individual pixel is relatively small i.e., to a large extent visual contribution of a pixel can be predicted using its neighbours.

A typical image/video transmission system is outlined in Figure 1. The objective of the source encoder is to exploit the redundancies in image data to provide compression. In other words, the source encoder reduces the entropy, which in our case means decrease in the average number of bits required to represent the image. On the contrary, the channel encoder adds redundancy to the output of the source encoder in order to enhance the reliability of the transmission. Clearly, both these high-level blocks have contradictory objectives and their interplay is an active research area. However, discussion on joint source channel coding is out of the scope of this document and this document mainly focuses on the transformation block in the source encoder. Nevertheless, pertinent details about other blocks will be provided as required.

The bases of the wavelet transform, the wavelets, are generated from a basic wavelet function by dilations and translations. They satisfy an admissible condition so that the original signal can be reconstructed by the inverse wavelet transform. The wavelets also satisfy the regularity condition so that the wavelet coefficients decrease fast with decreases of the scale. The wavelet transform is not only local in time but also in frequency. To reduce the time bandwidth product of the wavelet transform output, the discrete wavelet transform with discrete dilations and translations of the continuous wavelets can be used. The orthonormal wavelet transform is implemented in the multi resolution signal analysis framework, which is based on the scaling functions. The discrete translates of the scaling functions form an orthonormal basis at each resolution level. The wavelet basis is generated from the scaling function basis. The two bases are mutually orthogonal at each resolution level. The scaling function is an averaging function. The orthogonal projection of a function onto the scaling function basis is an averaged approximation. The orthogonal projection onto the wavelet basis is the difference between two approximations at two adjacent resolution levels.

Volume 4 Issue VIII, August 2016
ISSN: 2321-9653

International Journal for Research in Applied Science & Engineering Technology (IJRASET)

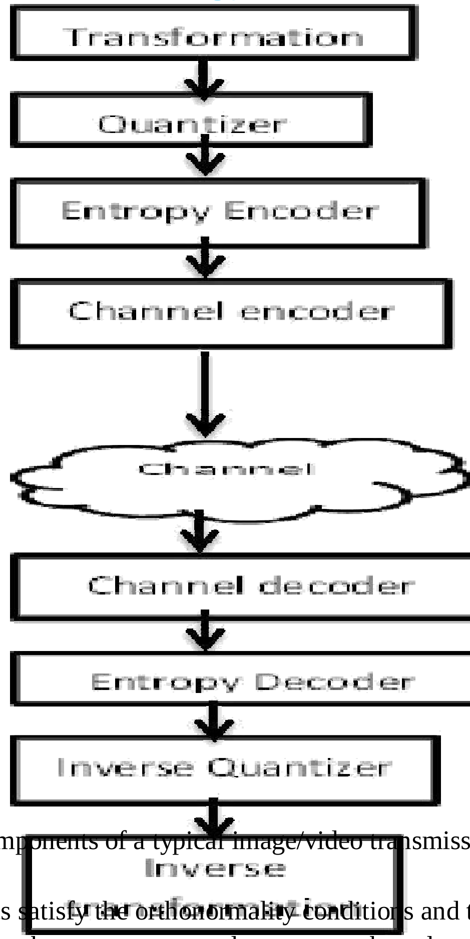


Fig.1.Components of a typical image/video transmission system

Both the scaling functions and the wavelets satisfy the orthonormality conditions and the regularity conditions. The discrete wavelet transform (DWT) is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. Its derived features used for digital image texture analysis. Wavelets appear to be a suitable tool for this task because they allow analysis of images at various levels of resolution. The main feature of DWT is a multi-scale representation of function. By using the wavelets, given function can be analysed at various levels of resolution. The DWT is also invertible and can be orthogonal. Wavelets seem to be effective for analysis of textures recorded with different resolution.

In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information (location in time). The discrete wavelet transform (DWT) has gained wide popularity due to its excellent decorrelation property; it's an effective tool for performing multi-resolution analysis of images. The capability of DWT makes multi-resolution image analysis, representation and coding more efficient. Day-by-day Discrete Wavelet Transform (DWT) is becoming more and more popular for digital image texture analysis and appears to be a suitable tool for analysis of images at various level of resolution. The first DWT was invented by the Hungarian mathematician Alfred Haar. For an input represented by a list of 2^n numbers, the Haar wavelet transform may be considered to simply pair up input values, storing the difference and passing the sum. This process is repeated recursively, pairing up the sums to provide the next scale: finally resulting in $2^n - 1$ differences and one final sum.

The most commonly used set of discrete wavelet transforms was formulated by the Belgian mathematician Ingrid Daubechies in 1988. This formulation is based on the use of recurrence relations to generate progressively finer discrete samplings of an implicit mother wavelet function; each resolution is twice that of the previous scale. In her seminal paper, Daubechies derives a family of wavelets, the first of which is the Haar wavelet. Interest in this field has exploded since then, and many variations of Daubechies' original wavelets were developed. Other forms of discrete wavelet transform include the non- or undecimated wavelet transform (where down sampling is omitted), the Newland transform (where an orthonormal basis of wavelets is formed from appropriately

Volume 4 Issue VIII, August 2016
ISSN: 2321-9653

constructed top-hat filters in frequency space). Wavelet packet transforms are also related to the discrete wavelet transform. Complex wavelet transform is another form.

Discrete wavelet transform as reported by Zervas et al. there are three basic architectures for the two-dimensional DWT: level-by-level, line-based, and block-based architectures. In implementing the 2-D DWT, a recursive algorithm based on the line based architectures is used. The image to be transformed is stored in a 2-D array. Once all the elements in a row is obtained, the convolution is performed in that particular row. The process of row-wise convolution will divide the given image into two parts with the number of rows in each part equal to half that of the image. This matrix is again subjected to a recursive line-based convolution, but this time column-wise. The result will DWT coefficients corresponding to the image, with the approximation coefficient occupying the top-left quarter of the matrix, horizontal coefficients occupying the bottom-left quarter of the matrix, vertical coefficients occupying the top-right quarter of the matrix and the diagonal coefficients occupying the bottom-right quarter of the matrix.

Image processing and analysis based on the continuous or discrete image transforms are classic techniques. The image transforms are widely used in image filtering, data description, etc. Nowadays the wavelet theorems make up very popular methods of image processing, denoising and compression. Considering that the Haar functions are the simplest wavelets, these forms are used in many methods of discrete image transforms and processing. The image transform theory is a well-known area characterized by a precise mathematical background, but in many cases some transforms have particular properties which are not still investigated. This paper for the first time presents graphic dependences between parts of Haar and wavelets spectra. It also presents a method of image analysis by means of the wavelets–Haar spectrum. Some properties of the Haar and wavelets spectrum were investigated. The extractions of image features immediately from spectral coefficients distribution were shown. In this paper it is presented that two–dimensional both, the Haar and wavelets functions products man be treated as extractors of particular image features. Furthermore, it is also shown that some coefficients from both spectra are proportional, which simplify slightly computations and analyses.Haar functions are used since 1910. They were introduced by Hungarian mathematician Alfred Haar. Nowadays, several definitions of the Haar functions and various generalizations as well as some modifications were published and used. One of the best modifications, which was introduced, is the lifting scheme.

These transforms have been applied, for instance, to spectral techniques for multiple– valued logic, image coding, edge extraction, etc. Over the past few years, a variety of powerful and sophisticated wavelet–based schemes for image compression, as discussed later, were developed and implemented. Wavelet scheme gives many advantages, which are used in the JPEG–2000 standard as wavelet–based compression algorithms. Generally, wavelets, with all generalizations and modifications, were intended to adapt this concept to some practical applications. The Discrete Wavelet Transform uses the Haar functions in image coding, edge extraction and binary logic design and is one of the most promising technique today. The non–sinusoidal Haar transform is the complete unitary transform. It is local, thus can be used for data compression of non-stationary “spiky” signals. The digital images may be treated as such “spiky” signals. Unfortunately, the Haar Transform has poor energy compaction for image, therefore in practice, basic Haar transform is not used in image compression. One should remember that researches in this topic are still in progress and everyday new solutions and improvements are found an outstanding property of the Haar functions is that except function haar(0, t),the i–th Haar function can be generated by the restriction of the (j − 1)–th function to be half of the interval where it is different from zero, by multiplication with p2 and scaling over the interval [0, 1].These properties give considerable interest of the Haar function, since they closely relate them to the wavelet theory. In this setting, the first two Haar functions are called the global functions, while all the others are denoted as the local functions. Hence, the Haar function, which is an odd rectangular pulse pair, is the simplest and oldest wavelet.

The motivation for using the discrete wavelet transform is to obtain information that is more discriminating by providing a different resolution at different parts of the time–frequency plane. The wavelet transforms allow the partitioning of the time-frequency domain into nonuniform tiles in connection with the time spectral contents of the signal. The wavelet methods are strongly connected with classical basis of the Haar functions; scaling and dilation of a basic wavelet can generate the basis Haar functions.

Def 1. Let Ψ: R→ R, the Haar wavelet function is defined by the formula

$$\Psi(t) = \begin{cases} 1, & \text{for } t \in [0, \frac{1}{2}), \\ -1, & \text{for } t \in [\frac{1}{2}, 1), \\ 0, & \text{otherwise.} \end{cases}$$

Volume 4 Issue VIII, August 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Taking into account the Definition, any Haar function (except function haar (0, t)) from basis may be generated by means of the formulas:

$$\Psi_i^j(t) = \sqrt{2^j}\Psi(2^j t - i), \qquad i = 0, 1, \ldots, 2^j - 1$$

and $j = 0, 1, \ldots, \log_2 N - 1$.
The constant $\sqrt{2^j}$ is chosen so that the scalar product $< \Psi_i^j, \Psi_i^j >= 1,\ \Psi_i^j \in L^2(\mathbf{R})$. If one considers the wavelet function on other intervals than (0, 1), the normalization constant will be different. For example:

$$\Psi_0^0 = haar(1,t),\ \Psi_0^1 = haar(2,t),\ \Psi_1^1 = haar(3,t),$$

$$\Psi_0^2 = haar(4,t),\ \Psi_1^2 = haar(5,t),\ \Psi_2^2 = haar(6,t),\ \Psi_3^2 = h$$

Generally from this example follows that functions $\Psi_i^j(t)$ are orthogonal to one another. Hence, we obtain linear

Span of vector space $W^j = span\{\Psi_i^j\}_{i=0,\ldots,2^j-1}$. A collection of linearly independent functions spanning W^j is called wavelets. $\{\Psi_i^j(t)\}_{i=0,\ldots,2^j-1}$

Def. 2. Let Φ: R→ R, the Haar scaling function is defined by the formula

$$\Phi(t) = \begin{cases} 1, & \text{for } t \in [0,1), \\ 0, & \text{for } t \notin [0,1). \end{cases}$$

Similarly to the properties of the wavelet function, for scaling function one can define the family of functions:

$$\Phi_i^j(t) = \sqrt{2^j}\Phi(2^j t - i), \qquad i = 0, 1, \ldots, 2^j - 1 \text{ and } j = 0, 1, \ldots, \log_2$$

The constant $\sqrt{2^j}$ is chosen so that the scalar product $< \Phi_i^j, \Phi_i^j >= 1,\ \Phi_i^j \in L^2(\mathbf{R})$. The index j refers to dilation and index i refers to translation. Hence, we obtain linear span of vector space

$V^j = span\{\Phi_i^j\}_{i=0,\ldots,2^j-1}$. The basic functions from the space V^j is called scaling functions. In multi resolution analysis the Haar basis has important property: $V^j = V^{j-1} \oplus W^{j-1}$,

Where stands for orthogonality of V^j and W^j spaces.

From Definitions 1 and 2 follows, that vector space W^j can be treated as the orthogonal complement of V^j in V^{j+1}. In other words, let W^j be the space of all functions in V^{j+1} that are orthogonal to all functions in V^j. Therefore, the basic functions Ψ_i^j of W^j together with the basic functions Φ_i^j of V^j form a basis for V^{j+1} and every basis function Ψ_i^j of W^j is orthogonal to every basis function Φ_i^j of V^j.

From the properties of the Haar functions, described above, follows that basic wavelet is progressively narrowed (reduced in scale) by powers of two. Each smaller wavelet is then translated by increments equal to its width, so that the complete set of wavelets at

www.ijraset.com Volume 4 Issue VIII, August 2016
IC Value: 13.98 ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

any scale completely covers the interval.

From mentioned equations one can conclude, that the basic wavelet is scaled down by powers of 2, but its amplitude is scaled up by powers of √2.

The discrete wavelet transform (DWT) is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. It is a tool that separates data into different frequency components, and then studies each component with resolution matched to its scale.DWT is computed with a cascade of filtering followed by a factor 2 sub sampling (fig.2)

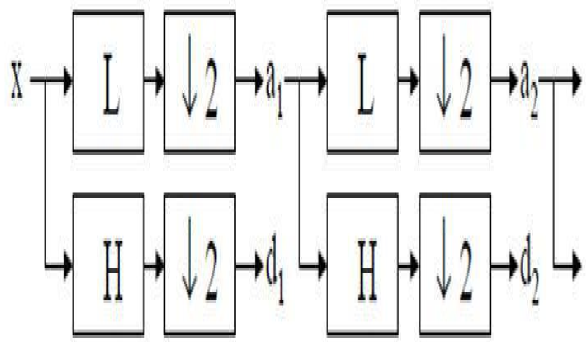


Fig.2.DWT Tree

H and *L* denote high and low-pass filters respectively, down arrow with 2 denotes sub sampling. Outputs of these filters are given by equations (1) and (2)

$$a_{j+1}[p] = \sum_{n=-\infty}^{+\infty} l[n-2p]a_j[n]$$

$$d_{j+1}[p] = \sum_{n=-\infty}^{+\infty} h[n-2p]a_j[n]$$

Elements a_j are used for next step (scale) of the transform and elements *dj*, called wavelet coefficients, determine output of the transform. *l[n]* and *h[n]* are coefficients of low and high-pas filters respectively One can assume that on scale *j+1* there is only half from number of *a* and *d* elements on scale *j*. This causes that DWT can be done until only two a_j elements remain in the analysed signal These elements are called scaling function coefficients. DWT algorithm for two-dimensional pictures is similar. The DWT is performed firstly for all image rows and then for all columns.(fig.3)

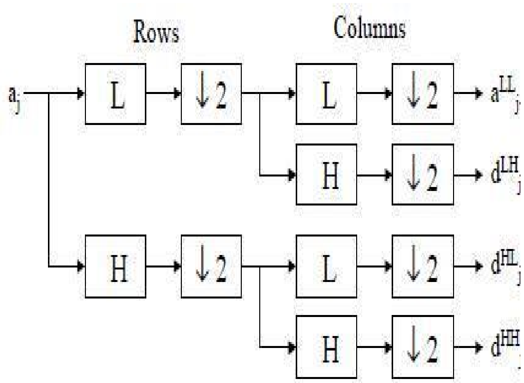


Fig.3.Wavelet decomposition of two-dimensional picture

Volume 4 Issue VIII, August 2016
ISSN: 2321-9653
International Journal for Research in Applied Science & Engineering Technology (IJRASET)

The main feature of DWT is multiscale representation of function. By using the wavelets, given function can be analysed at various levels of resolution. The DWT is also invertible and can be orthogonal. Wavelets seem to be effective for analysis of textures recorded with different resolution. It is very important problem in NMR imaging, because high-resolution images require long time of acquisition. This causes an increase of artefacts caused by patient movements, which should be avoided. There is an expectation that the proposed approach will provide a tool for fast, low resolution NMR medical diagnostic. In this work only one set of DWT derived features is considered. It is a vector, which contains energies of wavelet coefficients calculated in sub bands at successive scales. A special module for Mazda program was developed which allows evaluating of those features.

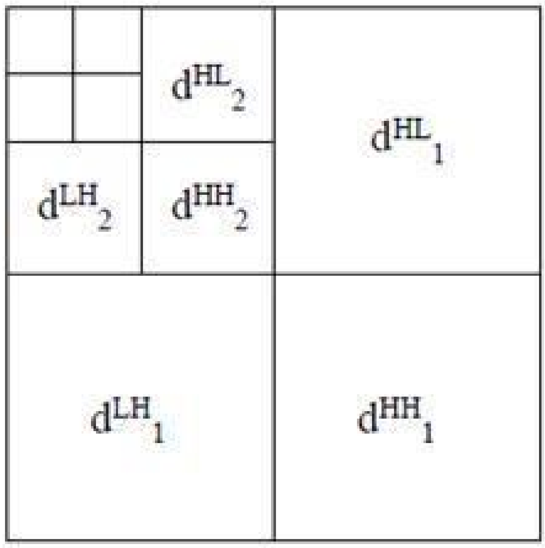


Fig.4.Sub band image

Sub band image *aLL* is used only for DWT calculation at the next scale. For the given image, the maximum of 8 scales can be calculated. The Harr wavelet is calculated only if output sub bands have dimensions at least 8 by 8 points. In the next step, energy (3) of *dLH*, *dHL* and *dHH* is calculated at any considered sale in marked ROIs.

$$E_{subband,scale} = \frac{\sum_{x,y \in ROI} \left(d_{x,y}^{subband}\right)^2}{n} \qquad (3)$$

Where *n* is the number of pixels in ROI, both at given scale and sub band.

A probabilistic estimation bias (PEB) circuit for a fixed-width two's complement Booth multiplier is proposed for this investigation. The implementations developed for this study to indicate that traditional Booth encoded multipliers are superior in layout area, power, and delay to non-Booth encoded multiplier. Fixed Width multipliers are widely used in digital signal processing systems, such as discrete cosine transform (DCT), finite-impulse-response filter, and fast Fourier transform. Nevertheless, the computation error is introduced if the least significant (LS) half part is directly truncated. To reduce the computation error, many compensation techniques were presented for array multipliers. There is an apparently tradeoff between accuracy and hardware complexity. Recently, compensation works have been increasing by focusing on reducing truncation error on the Booth multiplier.

III. PROPOSED SYSTEM

A probabilistic estimation bias (PEB) circuit for a fixed-width two's complement Booth multiplier is proposed for this investigation. The implementations developed for this study to indicate that traditional Booth encoded multipliers are superior in layout area, power, and delay to non-Booth encoded multiplier. In this brief, a Probabilistic Estimation bias (PEB) circuit for a fixed width two's complement is proposed. The proposed PEB circuit is derived from theoretical computation. This circuit provide a smaller area and lower truncation error compared with existing system. Mostly implemented in a 2- D DWT core using proposed PEB booth multiplier. Fixed width multiplier generates an output with the same width as the input. They are widely used in digital signal processing systems. The computation error is introduced if the least significant (LS) half part is directly truncated. To reduce the computation error, many compensation techniques were presented for array multipliers. There is an apparently trade-off between accuracy and hardware complexity. Recently, compensation works have been increasing focused on reducing the truncation error on the booth multiplier .In presented statistical and linear regression analysis to reduce the hardware complexity. However, the truncation error was partly depressed because the estimation information that came from the truncated part is limited. In addition, the low-error and area-efficient PEB circuit is obtained based on the simple and systematic procedure. In this way, the time-consuming exhaustion simulation and the heuristic process of the compensation circuit can be avoided. Furthermore, the hardware efficiency and low error are validated through our simulation results. The main advantage of this method has provided smaller area and smaller truncation errors.

IV. CALCULATIONS

A. Find out the length of the sequence or sample (M).

B. If the sequence length M=4 , then

$$M=2^{j} \Rightarrow M=2^{2} \quad j=2$$

C. If J=2, then J=0,1,2,………,j-1 and K=0,1,2,………,2^{J-1} that is, J=0,1

D. If J=0 then K=0 if J=1 then $k=2^{1}-2^{0}=1$ therefore K=0,1

E. Implementing the Haar Transformation Matrix [$h_k(z)$] or H matrix for M=4,where k=0,1,…….,M-1 i.e. k=0,1,2,3

F. The z varies from 0<=z<=1therefore z=>0/M,1/M,………..,M-1/M,i.e. z= 0 , ¼ , ½ , ¾

G. Here $M=2^{n}$, i.e. $M=2^{2}=4$ where n=2.

H. The value of p varies from 0<=p<=n-1 therefore the value p=0,1

I. If p=0 then q should be 0 or 1;if p not equal to 0 then q varies from $1<=q<=2^{p}$

J. Here we have an equation $k=2^{p}+q-1$ so we get $q=k-2^{p}+1$

K. For Different values of k find out the values of p and q by using above conditions.

L. For H matrix the values ranges $2^{p/2}$; $q-1/2^{p} <= z < q-0.5/2^{p}$ $h_k(z)= -2^{p/2}$; $q-0.5/2^{p} <= z < q/2^{p}$ 0 ; otherwise

M. From the H matrix we can find the Discrete wavelet Transformed values by the equation :

$$Ꞷ_{\varphi}(j,k)= 1/\sqrt{M} \sum_{n=0}^{M-1} f(n)\, \Psi_{j,k}(n)$$

Where f(n) is values of input sequence $\Psi_{j,k}(n)$ is the values of H matrix

V. CONCLUSION

Power and area consumption is the main advantage of this paper. The techniques implemented in this paper are cheap and very easy to be practiced. PEB circuit provides a smaller area and a lower truncation errors compared with existing system. We intend to implement PEB method for reducing the truncation error in fixed width booth multiplier. It is accurate and more efficient. We have first derived the PEB formula and applied the probabilistic analysis for the truncated two’s compliment fixed-width booth multiplier. So a simple and systematic procedure has been presented to design the compensation circuit based on PEB formula and probabilistic analysis. The realization of our PEB circuit does not need exhaustive simulations and heuristic compensation strategies. Image compression scheme based on discrete wavelet transform is proposed in this research which provides sufficient high compression ratios with no appreciable degradation of image quality. The effectiveness and robustness of this approach has been justified using a set of real images. The images are taken with a digital camera. To demonstrate the performance of the proposed method, a comparison between the proposed technique and other common compression techniques has been revealed. From the experimental results it is evident that, the proposed compression technique gives better performance compared to other traditional techniques. Wavelets are better suited to time-limited data and wavelet based compression technique maintains better

Volume 4 Issue VIII, August 2016
ISSN: 2321-9653

image quality by reducing errors. The future direction of this research is to implement a compression technique using neural network.

REFERENCES

[1] Y. C. Lim, "Single-precision multiplier with reduced circuit complexity for signal processing applications," IEEE Trans. Comput., vol. 41, no. 10, pp. 1333–1336, Oct. 1992.

[2] J. Schulte and E. E. Swartzlander, Jr., "Truncated multiplication with correction constant," in VLSI Symp. Tech. Dig., 1993, pp. 388–396. S. S. Kidambi, F. El-Guibaly, and A. Antoniou, "Area-efficient multipliers for digital signal processing applications," IEEE Trans. Circuits Syst. II, Analog Digit. Signal Process, vol. 43, no. 2, pp. 90–95, Feb. 1996.

[3] J. M. Jou, S. R. Kuang, and R. D. Chen, "Design of lower-error fixed width multipliers for DSP applications," IEEE Trans. Circuits Syst. II, Analog Digit. Signal Process, vol. 46, no. 6, pp. 836– 842, Jun. 1999.

[4] L. D. Van, S. S. Wang, and W. S. Feng, "Design of the lower-error fixed width multiplier and its application," IEEE Trans. Circuits Syst. II, Analog Digit. Signal Process, vol. 47, no. 10, pp. 1112– 1118, Oct. 2000.

[5] L. D. Van and C. C. Yang, "Generalized low-error area-efficient fixed width multipliers," IEEE Trans. Circuits Syst. I, Reg. Papers, vol. 52, no. 8, pp. 1608–1619, Aug. 2005.

[6] N. Petra, D. D. Caro, V. Garofalo, E. Napoli, and A. G. M. Strollo, "Truncated binary multipliers with variable correction and minimum mean square error," IEEE Trans. Circuits Syst. I, Reg. Papers, vol. 57, no. 6, pp. 1312–1325, Jun. 2010.

[7] S. J. Jou, M. H. Tsai, and Y. L. Tsao, "Low-error reduced-width Booth multipliers for DSP applications," IEEE Trans. Circuits Syst. I, Fundam. Theory Appl., vol. 50, no. 11, pp. 1470–1474, Nov. 2003.

[8] K. J. Cho, K. C. Lee, J. G. Chung, and K. K. Parhi, "Design of low-error fixed-width modified Booth multiplier," IEEE Trans.Very Large Scale Integer. (VLSI) Syst., vol. 12, no. 5, pp. 522–531, May 2004.

[9] T. B. Juang and S. F. Hsiao, "Low-error carry-free fixed-width multipliers with low-cost compensation circuits," IEEE Trans. Circuits Syst. II, Exp. Briefs, vol. 52, no. 6, pp. 299–303, Jun. 2005.

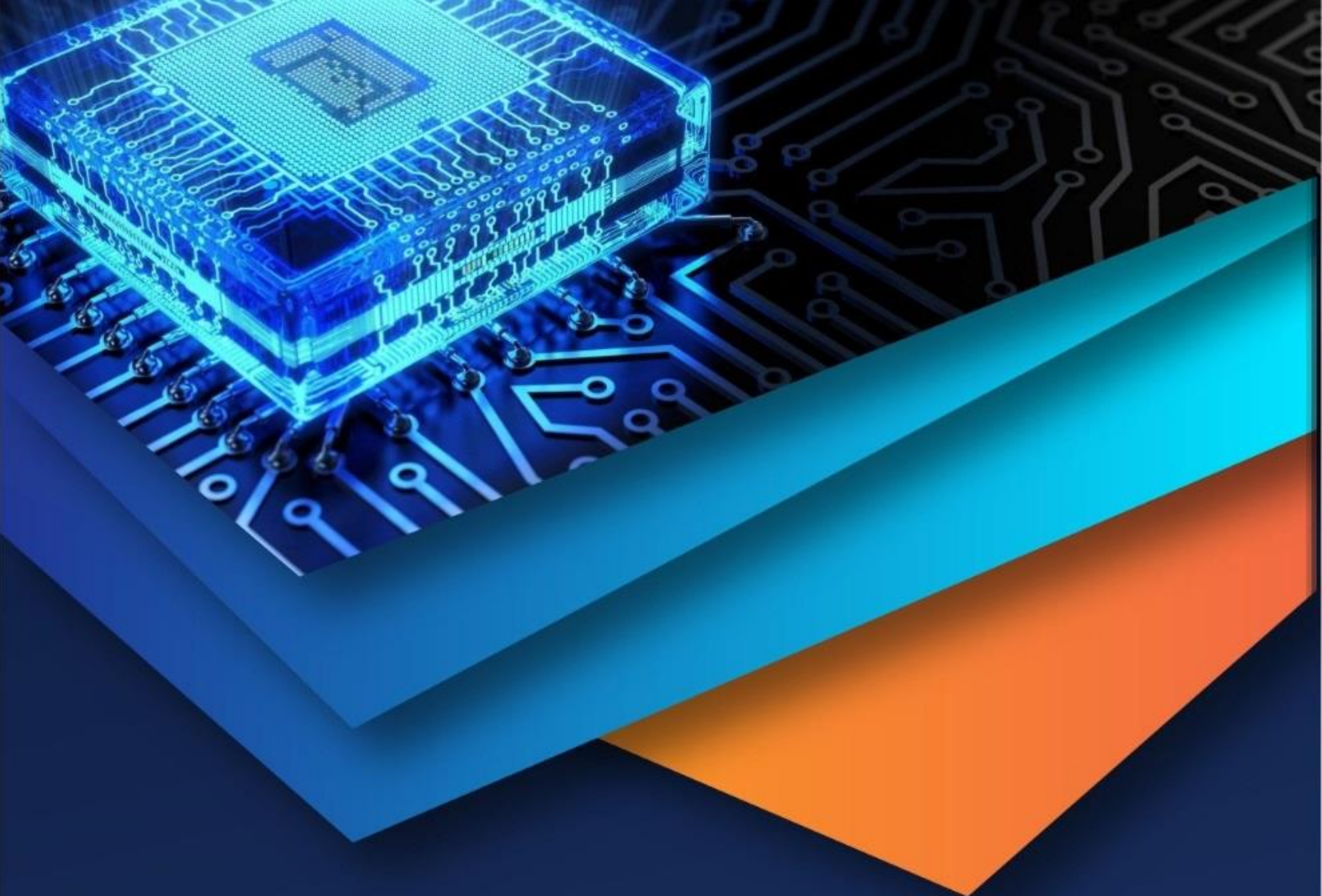
[10] K. K. Parhi, J. G. Chung, K. C. Lee, and K. J. Cho, "Low-error fixed-width modified Booth multiplier," U.S. Patent 334 200, Feb. 19, 2008.

[11] H. A. Huang, Y. C. Liao, and H. C. Chang, "A self-compensation fixed width Booth multiplier and its 128-point FFT applications," in Proc. IEEE ISCAS, 2006, pp. 3538–3541.

[12] M. A. Song, L. D. Van, and S. Y. Kuo, "Adaptive low-error fixed-width Booth multipliers," IEICE Trans. Fundam., vol. E90-A, no. 6, pp. 1180– 1187, Jun. 2007.

[13] J. P. Wang, S. R. Kuang, and S. C. Liang, "High-accuracy fixed width modified Booth multipliers for lossy applications," IEEE Trans. Very Large Scale Integer. (VLSI) Syst., vol. 19, no. 1, pp. 52–60, Jan. 2011.

[14] B. Parhami, Computer Arithmetic: Algorithms and Hardware Designs.. Oxford, U.K.: Oxford Univ. Press, 2000.



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

TOGETHER WE REACH THE GOAL

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY