CHAPTER 3

WAVELET DECOMPOSITION USING HAAR WAVELET

3.1 WAVELET

Wavelet as a subject is highly interdisciplinary and it draws in crucial ways on ideas from the outside world. The working of wavelet in image processing is analogous to the working of human eyes. Depending on the location of the observation, one may perceive a forest differently. If the forest was observed from the top of a skyscraper it will be observed as a blob of green. If it was observed in a moving car, it will be observed as the trees in the forest flashing through, thus the trees are now recognized. Nonetheless, if it is observed by one who actually walks around it, then more details of the trees such as leaves and branches and perhaps even the monkey on the top of the coconut tree may be observed. Furthermore, pulling out a magnifying glass may even make it possible to observe the texture of the trees and other little details that cannot perceived by bare human eye. Wavelet transform is an efficient tool to represent an image. It has been developed to allow some temporal or spatial information.

3.2 WAVELET DECOMPOSITION

Wavelets are generated from one single function (basis function) called the mother wavelet. Mother Wavelet is a prototype for generating the other window functions. The mother wavelet is scaled or dilated by a factor of a and translated or shifted by a factor of b to give:

$$\Psi_{a,b}(t) = \left(\frac{1}{\sqrt{|a|}}\right) \times \Psi\left(\frac{t-b}{a}\right) \tag{3.1}$$

where a and b are two arbitrary real numbers that represent the dilations and translations parameters, respectively in the time axis.

The idea of the wavelet transform is to use a family of functions localized in both time and frequency. Wavelet transform represents an image as a sum of wavelet functions with different location and scales. Any decomposition of an image into wavelets involves a pair of waveforms. These represent the high frequencies corresponding to the detailed parts of an image called as wavelet function. The other represent low frequencies or smooth parts of an image called scaling function. To accomplish this, the transform function known as the mother wavelet, is modified by translations and dilation. In order to be classed as a wavelet, the analyzing function $\Psi(t)$ must satisfy the following admissibility condition.

$$C(\Psi) = \int_{-\infty}^{\infty} \frac{|\Psi(\omega)|^2}{|\omega|} d\omega < \infty \tag{3.2}$$

Essentially, this admissibility criteria, ensures that the function called the mother wavelet is a band pass filter. From this function, a family of functions which are the actual wavelet can be derived according to the following equation.

$$\Psi_{(a,b)} = \left|a^{-1/2}\right| \Psi\left(\frac{\mathrm{t-b}}{\mathrm{a}}\right) \tag{3.3}$$

The wavelet transform theory can be generalized to any dimensionality desired. However, in this section only the two dimensional, discrete WT, with important applications in image processing is considered.

The two dimensional multiresolution analysis which describes the transform is derived directly from the one dimensional equivalent. It defines the space $L^2(R^2)$ as a hierarchy of embedded subspacesV_j, such that none of the subspaces intersect, and for each function $f(t)$ belongs to V_j, $t \in R_2$ the following condition holds:

$$f(t) \in V_j \Rightarrow f(dt) \in V_{j-1} \tag{3.4}$$

Where D is a 2 X 2 matrix with integer elements, and Eigen values with absolute values greater than one. The individual elements of the matrix indicate which samples of $f(t)$ are kept and which are discarded. If N and u are the points in the input and output images respectively, this can be represented as

$$N = D.u \tag{3.5}$$

The two dimensional wavelet is calculated by filtering the sampled signal $f(k)$ with the filters $h(k)$ and $g^{|}(k), t = 1,2, \ldots |D| - 1$. Down-sampling is performed after each such filtering operation. This entire procedure is then performed successively on the approximation signal to the required number of levels j.

3.2.1 Properties of Wavelet

Various properties of wavelet transforms is described below:

1. Regularity.
2. The window for a function is the smallest space-set or time set out which function is identically zero.

3. The order of the polynomial that can be approximated is determined by number of vanishing moments of wavelets and is useful for image analysis.
4. The symmetry of the filters is given by wavelet symmetry. It helps to avoid the phasing in image processing. The Haar Wavelet is the only symmetric wavelet among orthogonal. For bi-orthogonal wavelets both wavelet function and scaling function that are either symmetric or anti-symmetric can be synthesized.
5. Orthogonality: Orthogonal filters lead to orthogonal wavelet basis functions. Hence the resulting wavelet transform is energy preserving. This implies that the mean square error introduced during the quantization of the DWT coefficient is equal to the MSE in the reconstructed signal.
6. Filter Length: Shorter synthesis basis functions are desired for minimizing distortion that affects the subjective quality of the image. Longer filters are responsible for ringing noise in the reconstructed image.
7. Vanishing order: It is a measure of the compaction property of the wavelets. A higher vanishing moment corresponds to better accuracy of approximation at a particular resolution. Thus, the frequency sub-band captures the input signal more accurately by concentrating a larger percentage of the image's energy in the LL sub-band.
8. Non-smooth basis function introduces artificial discontinuities under quantization. These discontinuities are the spurious artifacts in the reconstructed images.
9. Group delay difference: It measures the deviation in group delay of the orthogonal wavelets from the linear phase group delay. It can be calculated as the mean-squared error of the

filters actual group delay from the ideal group delay in the pass band.

3.2.2 Wavelet Families

There are many members in the wavelet family. A few of them that are generally found to be more useful are given below:

Haar Wavelet is one of the oldest and simplest wavelet. Therefore, any discussion of the wavelets starts with the Haar Wavelet. Daubechies wavelets are the also popular and they represent the foundation of wavelet signal processing and are used in numerous applications. These are also called Maxflat wavelets as their frequency responses have maximum flatness at frequencies 0 and R. This is a very desirable property in some applications. The Haar, Daubechies, Symlets and Coiflets are compactly supported orthogonal wavelets. These wavelets along with Meyer wavelets are capable of perfect reconstruction. The Meyer, Morlet and Mexican Hat wavelets are symmetric in shape. The wavelets are chosen based on their shapes and their ability to analyze the signal in a particular application. Haar wavelet is discontinuous and resembles a step function.

Daubechies: Daubechies are compactly supported orthogonal wavelets and found application in DWT.

Coiflets: The wavelet function has 2N moments equal to 0 and the scaling function has 2N-1 moments equal to 0. The two functions have a support of length 6N-1.

Biorthogonal Wavelet: This family of wavelets exhibits the property of linear phase, which is needed for signal and image reconstruction.

Interesting properties are derived by employing two wavelets, one for decomposition and the other for reconstruction instead of the same single one.

Symlets: The symlets are nearly symmetrical wavelet. The properties of the two wavelet families are similar.

Morlet: This wavelet has no scaling function.

Mexican Hat: This wavelet has no scaling function and is derived from a function that is proportional to the second derivative function of the Gaussian probability density function.

Meyer Wavelet: The Meyer wavelet and scaling function are defined in the frequency domain.

Some other wavelets available are Reverse Biorthogonal, Gaussian derivatives family, FIR based approximation of the Meyer wavelet. Some complex wavelet families available are Gaussian derivatives, Morlet, Frequency B-Spline, Shannon, etc.

3.2.3 Why Prefer Wavelet?

An image can be decomposed at different levels of resolution and can be sequentially processed from low resolution to high resolution using wavelet decomposition because wavelets are localized in both time (space) and frequency (scale) domains. Hence it is easy to capture local features in a signal. Another advantage of wavelet basis is that it supports multi resolution. With wavelet based decomposition, the window sizes vary and allow analyzing the signal at different resolution levels. Wavelet transform decomposes an image into various sub-images based on local frequency content. It represents an image as a sum of wavelet functions with different location and scales. Any decomposition of an image into wavelets involves a pair of waveforms. These represent the high frequencies corresponding to the detailed parts of an image called as wavelet function. The other represent low frequencies or smooth parts of an image called scaling function. The principle of the wavelet decomposition is to transform the original raw image into several components with single low-resolution component called "approximation" and the other components called "details" as shown in Figure 3.1. The approximation component is obtained after applying a bi-orthogonal low-pass wavelet in each direction i.e. horizontal and vertical followed by a sub-sampling of each image by a factor of two for each dimension. The details are obtained with the application of low-pass filter in one direction and a high-pass in the other or a high-pass in both the directions. The noise is mainly present in the details components. A higher level of decomposition is obtained by repeating the same operations on the approximation. For small details it is not obvious to a non-expert in the diagnosis of ultrasound images to know what is needed to eliminate or to preserve and enhance.

The basic approach of wavelet based image processing is to:

1. Compute the two-dimensional wavelet transform of an image.
2. Alter the transform coefficients.
3. Compute the inverse transform.

The images are considered to be matrices with N rows and M columns. At every level of decomposition the horizontal data is filtered, then the approximation and details produced from this are filtered on columns. At every level, four sub images are obtained, the approximation, the vertical detail, the horizontal detail and the diagonal detail. The next level of decomposition can be obtained by the decomposition of approximation sub-image. The multilevel decomposition of an image is given in Figure 3.2.

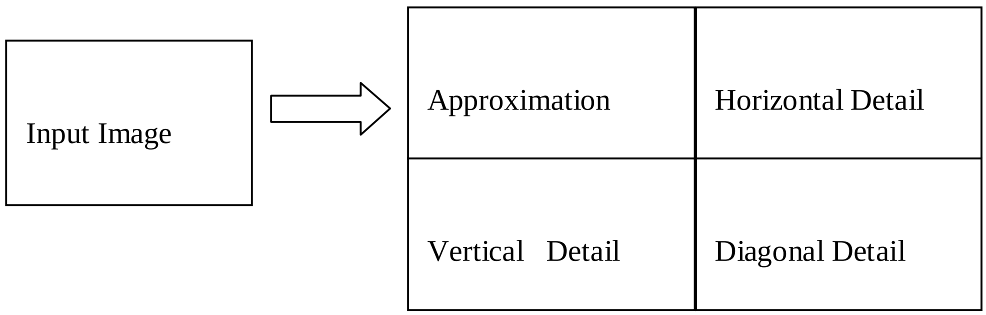

Figure 3.1 Wavelet Decomposition of a 2D Image

The horizontal edges of the original image are present in the horizontal detail coefficients of the upper-right quadrant. The vertical edges of the image can be similarly identified in the vertical detail coefficients of the lower-left quadrant. To combine this information into a single edge image, we simply zero the approximation coefficients of the generated transform. Compute the inverse of it and obtain the absolute value.

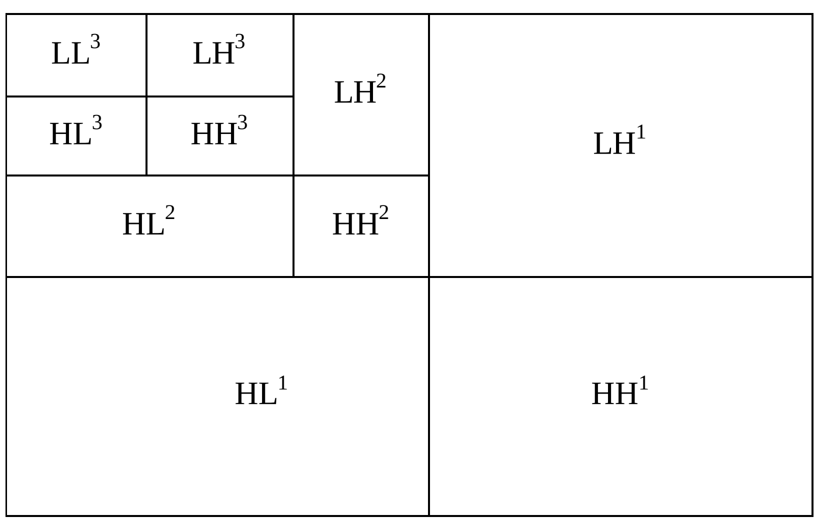

Figure 3.2 Multilevel Wavelet Decomposition of an Image

3.2.4 Choice of Mother Wavelet

The choice of wavelet bases depends on the signal. Signals coming from different sources have different characteristics. The wavelet basis functions are obtained from a single mother wavelet by translation and scaling. However, there is no single or universal mother wavelet function. The mother wavelet must simply satisfy a small set of conditions and is typically selected based on the domain of the signal or image processing problem. The best choices of wavelet bases are not clear for ultrasound placenta images. The problem is to represent typical signals with a small number of convenient computable functions. An investigation to choose the best wavelet for ultrasound images was performed on ultrasound placenta image. The majority of the wavelet bases which exist in the Matlab 7 version software were tested. The Haar wavelet is chosen for the decomposition of ultrasound placenta images. Higher levels of decomposition showed promising diagnostic features of the ultrasound placenta image.

3.3 HAAR WAVELET DECOMPOSITION OF ULTRASOUND PLACENTA

Haar wavelet basis can be used to represent an image by computing a wavelet transform. The pixel is averaged together pair-wise and is calculated to obtain the new resolution image with pixel values. Some information may be lost in the averaging process. The Haar wavelet transform is used to analyze images effectively and efficiently at various resolutions. It is used to get the approximation coefficients and detail coefficients at various levels. The Haar transform functions like a low-pass filter and a high-pass filter simultaneously.

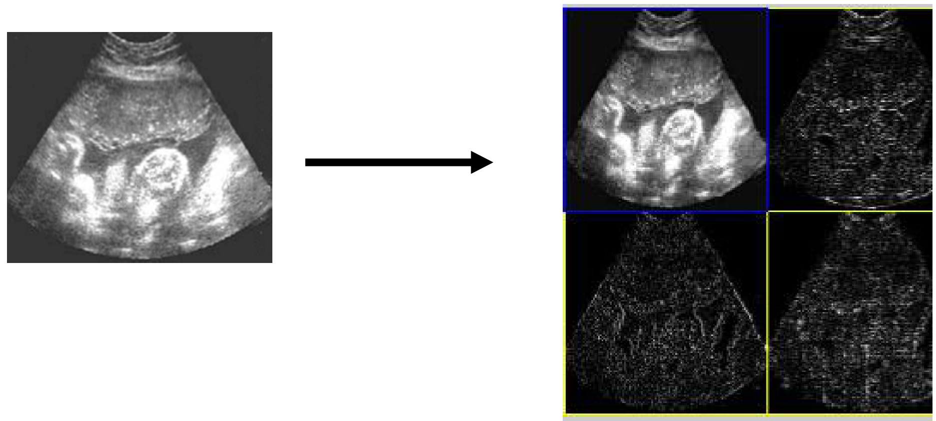

Figure 3.3 Level-1 Haar Wavelet Decomposition of an ultrasound placenta image

The ultrasound images of placenta with various gestational ages like 10 weeks, 12 weeks, 15 weeks, 17 weeks, and greater than 20 weeks are obtained from Chennai based Excel Diagnostic Scans, Aarthi Advanced C.T Scan & M.R.I, Mediscan Systems and Precision Diagnostics Pvt. Ltd. The placenta images thus obtained are demarcated into a normal placenta and GDM complicated placenta with the help of the sonologists. These images are then subjected to different levels of wavelet decomposition using different wavelets. The transverse scans of placenta are captured with differences of few seconds from the same mother. The multi-view ultrasound placenta is subjected to various levels (1, 2, 3 and 4) of wavelet decomposition. The synthesized image of the input image is obtained as a result. This synthesized image only forms the basis to Image fusion in the forthcoming chapter. The decomposition is done to extract the useful features from the multiview placenta. Still, these images cannot be used unless a quality assessment is done. To ensure the diagnostic accuracy of the images, quality evaluation metrics are used to evaluate the performance of the wavelets. The following Figure 3.3 is the representation of Level-1 Decomposition of ultrasound placenta using Haar.

Each of the transverse and longitudinal scans of the ultrasound placenta image is decomposed into approximate, horizontal, vertical and diagonal details. N levels of decomposition can be done. Here, 4-levels of decomposition are used. The multilevel decomposition of ultrasound placenta using Haar Wavelet is represented in the Figure 3.4. After that, quantization is done on the decomposed image where different quantization may be done on different components thus maximizing the amount of required details and ignoring the redundant details. This is done by thresholding where some coefficient values for pixels in images are thrown out or set to zero or some smoothing effect is done on the image matrix. In order to decide the most appropriate wavelet function for the ultrasound placenta, the image is decomposed using various wavelet functions. The wavelet function is chosen based on the results of image fusion quality measures.

Haar wavelet is the shortest and simplest basis and it provides satisfactory localization of the image characteristics. It is the only known wavelet that is compactly supported, orthogonal and symmetric.

Definition 1

$$I_{n,k} = [2^{-n}k, 2^{-n}(k+1)]$$

$$Let p(x) = X_{[0,1]}(x), and for each n, k \epsilon Z, define P_{n,k}(x) = 2^{n/2} p(2^n x - k)$$

The collection $\{\varphi_{n,k}(x)\}_{n,k\in z}$ is referred to as the system of Haar scaling functions.

a. For each $n, k \in Z, P_{n,k}(x) = 2^{n/2} X I_{n,k}(x)$ so that $P_{n,k}(x)$ is supported on the interval $I_{n,k}$ and does not vanish to the scaling function $P_{n,k}(x)$ as being associated with the interval $I_{n,k}$.

$$\int P_{n,k}(x)dx = \int I_{n,k}(x)dx = 2^{n/2}$$

and

$$\int \left|P_{n,k}(x)\right|^2 dx = \int I_{n,k} \left|P_{n,k}(x)\right|^2 dx = 1$$

Definition 2

$Let\ h(x) = X_{[0,1/2]}(x) - X_{[1/2,1]}(x)$
and for each $n,\quad k \in Z\ define\ h_{n,k}(x) = 2_{n/2} h(2^n x - k)$.

The collection $\{h_{n,k}(x)\}_{n,k} \in Z$ is referred to as the Haar system on R. For each $n \in Z$, the collection$\{h_{n,k}(x)\}_{n,k} \in Z$ is referred to as the system of scale j, Haar functions.

Definition 3

Given $J, N \in N$ with $J < N$ and a finite sequence $C_0 = \{C_0\}_k^{2^N-1}$, the discrete Haar transform of C_0 is defined by,

$$\{d_j(k) | 1 \le k \le 2^{N-j} - 1\} \cup \{C_J(k) || 0 \le k \le 2^{N-j} - 1\}$$

Where

$$C_j(k) = \frac{1}{\sqrt{2}}C_{j-1}(2k) + \frac{1}{\sqrt{2}}C_{j-1}(2k+1)d_j(k)$$

$$= \frac{1}{\sqrt{2}}C_{j-1}(2k) + \frac{1}{\sqrt{2}}C_{j-1}(2k+1)$$

$$C_{j-1}(2k) = \frac{1}{\sqrt{2}}C_j(k) + \frac{1}{\sqrt{2}}d_j(k)$$

$$C_{j-1}(2k+1) = \frac{1}{\sqrt{2}}C_j(k) - \frac{1}{\sqrt{2}}d_j(k)$$

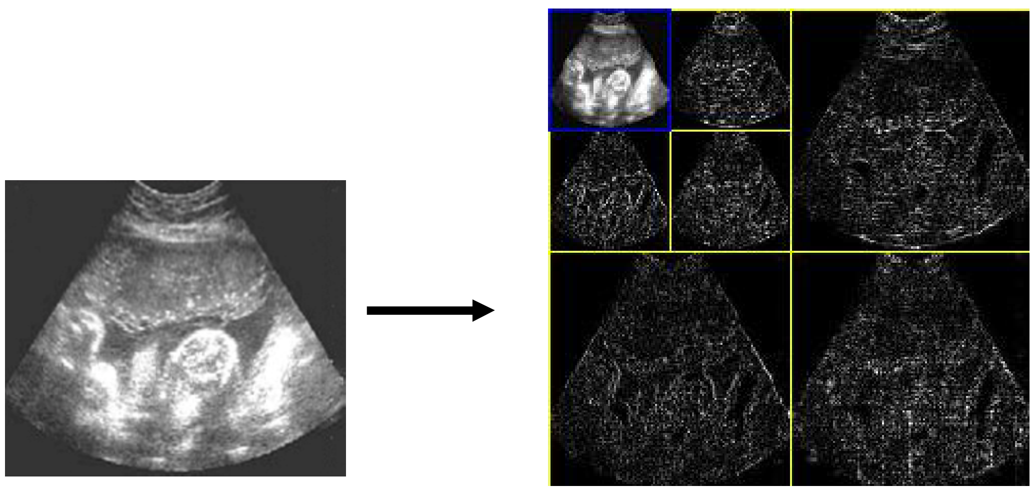

Figure 3.4 Multilevel Decomposition of Ultrasound Placenta using Haar Wavelet

The Haar system is defined as follows:

3.3.1 Haar Sub-band Coding

Sub band coding is a technique of decomposing the source signal into its constituent parts and decoding the parts separately. It is a system that isolates a constituent part corresponding to certain frequency is called a filter.

If it isolates the low frequency components, it is called a low-pass filter and isolates the high frequency components called a high-pass filter.

1. The image is passed through two filters: a low-pass filter and a high-pass filter. The low-pass filter lets only frequencies below a certain value through (i.e. $j < -1$) and the high-pass filter similarly allows only the highest frequencies in the image (i.e. $j = -1$). The wavelet coefficients for those frequencies (i.e. c-1, k) are then calculated.
2. Next, step 1 is repeated for those frequencies, which originally passed through the low-pass filter. In other words frequencies with $j = -2$ are extracted. Since the sampling rate required for storing these frequencies is now half the original only $n/4 = 256/4$ coefficients are required.
3. The filtering and sampling process is then repeated for all remaining frequencies ($j = -3..-8$) requiring progressively fewer and fewer coefficients to be kept ($n/8...n/256 = 256/8...256/256$). Finally, the coefficient of the sub-frequency is computed.

Haar Wavelets are basically same as Daubechies wavelet db1 or Daub4. Haar wavelets are example of compactly supported wavelets. The compact support of the Haar wavelets enables the Haar decomposition to have good time localization. Specifically, this means that the Haar coefficients are effective for locating jump discontinuities and also for the efficient representation of signals with small support. The Figure 3.5 is the Haar Wavelet Decomposition of multi-view (longitudinal and transverse) ultrasound placenta Image. The choice of the wavelet highly depends of the quality of the image generated. The Figure 3.7 gives the synthesized ultrasound images of placenta obtained from Haar, Daubechies and Symlet wavelet decomposition. The Haar wavelet is chosen in this research because of its good entropy and mutual information. However, the fact that they have dump discontinuities in particular in the poorly decaying Haar coefficients of smooth functions and the images reconstructed from subsets of the Haar coefficients.

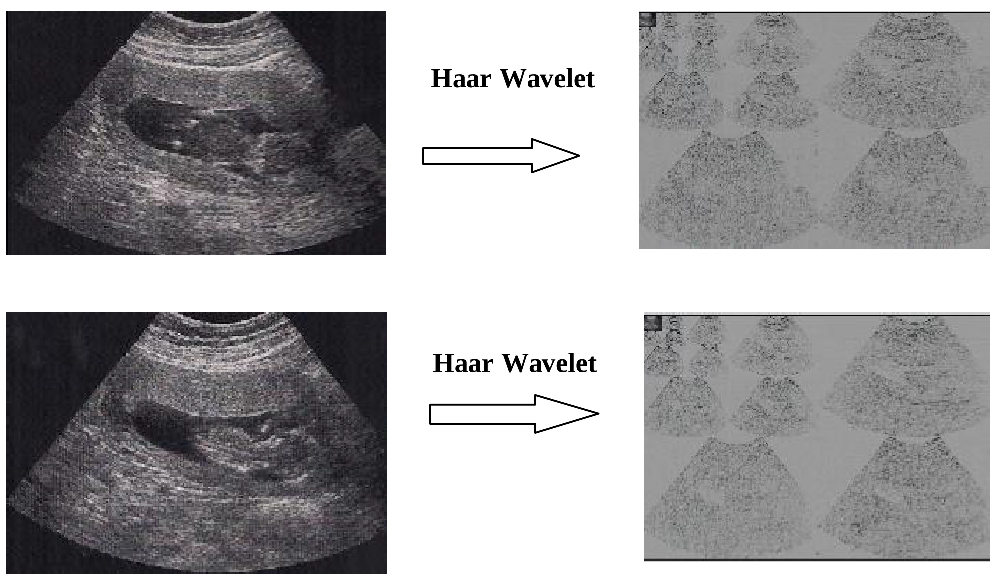

Figure 3.5 Haar Wavelet Decomposition of multi-view (longitudinal and transverse) ultrasound placenta Image

A 1-level wavelet transform of an NXM image can be represented as

$$f \mapsto \begin{pmatrix} a^1 & | & h^1 \\ - \quad - & & - \quad - \\ v^1 & | & d^1 \end{pmatrix} \tag{3.5}$$

$$a^1 = V_m^1 \otimes V_n^1 = \varphi(x,y) = \varphi(x)\varphi(y)$$

$$= \sum_i \sum_j h_i h_j \varphi(2x-i)\varphi(2y-j)$$

$$h^1 = V_m^1 \otimes V_n^1 = \Psi^H(x,y) = \Psi(x)\varphi(y)$$
$$= \sum_i \sum_j g_i h_j \Psi(2x-i)\varphi(2y-j)$$

$$v^1 = W_m^1 \otimes V_n^1 = \Psi v(x,y) = \varphi(x)\Psi(y)$$
$$= \sum_i \sum_j h_i g_j \varphi(2x-i)\Psi(2y-j)$$

$$d^1 = W_m^1 \otimes W_n^1 = \Psi^D(x,y) = \Psi(x)\varphi(y)$$
$$= \sum_i \sum_j g_i g_j \Psi(2x-i)\Psi(2y-j)$$

Where the sub imagesh^1, d^1, a^1 and v^1 each have dimensions of $N/2$ by $M/2$. Here a^1 denotes the first averaged time, which consists of average intensity values of the original image. h^1 denotes the first detail image of horizontal components, which consists of intensity difference along the horizontal axis of the original image d^1 denotes the first detail image of diagonal components which consists of intensity difference along the diagonal axis of the original image. The original image is reconstructed from the decomposed image by taking the sum of the averaged image and the detail and scaling by a scaling factor.

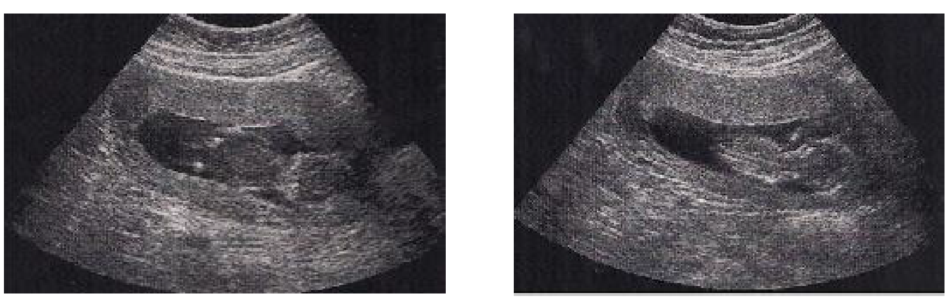

Figure 3.6 Multiview of Ultrasound Placenta complicated by GDM

Wavelet decomposition of image was performed the number of times the image can be divided by twice. The averaged image of the previous level is decomposed into the four sub images in each level of wavelet image decomposition. The image on the top left most corner get blurrier as it gets “averaged” out and also note the horizontal, vertical and diagonal components of the image.

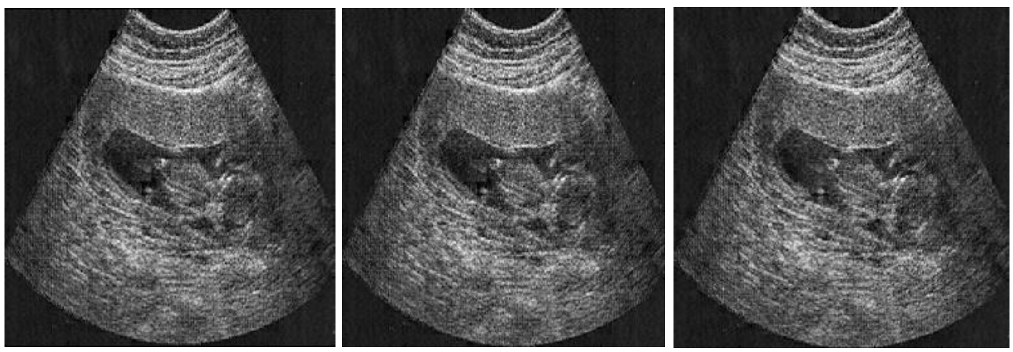

Figure 3.7 Images from left to right is the synthesized image of placenta obtained from Haar, Daubechies and Symlet Wavelet Decomposition (15 weeks gestational age)

3.4 RESULTS

The Figure 3.6 is the sample representation of the multi-view of the ultrasound placenta complicated by GDM. The quality of the image decomposed by different wavelets at various gestational age is compared in the tables below and as Figure 3.7. The Entropy, Normalized Cross Correlation, Structural Content, Spatial Frequency and Fusion Mutual Information is used as the quality measure in choosing the best wavelet for the characterizing the ultrasound placenta both normal and placenta complicated by GDM. Each has its importance in evaluating the image quality. The entropy of the synthesized image shows an increase in value when, the image is decomposed using Haar Wavelet, compared to the original input images. The measure of structural content of the image is low in the case of Haar. At every level of decomposition, Haar shows good performance in uniquely identifying the features of the placenta. The structural consent is more in the case of Daubechies. The image decomposed using Haar wavelet shows improved quality as the decomposition level increases. In the initial levels, the wavelets, Daubechies, Haar and Symlet show negligible variations in the results. It is also to be noted that placenta with GDM complications are identified by it high entropy when compared to the normal placenta.

The below Table 3.1 gives the quality evaluation metrics to identify the wavelet, that is suitable for the assessment of ultrasound placenta. Moreover, these metrics shows values with fewer differences between the gestational ages. As the gestational age increases, the metrics also increases.

Table 3.1 Quality Evaluation Metrics to evaluate the performance of Wavelets on normal vs. GDM Ultrasound placenta at 10 weeks of Gestational Age

Wavelet	PSNR	MSE	RMSE	STD	MEAN	Entropy	Class
Haar	33.5101	28.9784	5.3832	43.1958	112.3084	7.4205	Normal
Daubechies	33.4174	29.6035	5.4409	43.054	112.2816	7.3155	
Symlet	33.2889	30.4926	5.522	42.1112	106.5676	7.382	
Haar	33.5476	28.729	5.3599	42.4914	106.5915	7.4491	GDM
Daubechies	34.4057	23.5781	4.8557	42.4914	106.6384	7.3894	
Symlet	33.4628	29.2956	5.4125	44.1209	111.89	7.3894	

The values of PSNR, MSE, RMSE, STD, MEAN, ENTROPY which is recorded in the Table 3.1, Table 3.2, Table 3.3, Table 3.4 and Table 3.5 is obtained using the equations 4.11, 4.15, 4.10, 4.7, 4.6 and 4.9.

Table 3.2 Quality Evaluation Metrics to evaluate the performance of Wavelets on normal vs. GDM Ultrasound placenta at 12 weeks of Gestational Age

Wavelet	PSNR	MSE	RMSE	STD	MEAN	Entropy	Class
Haar	33.7862	27.1932	5.2147	63.8662	121.8244	7.4258	Normal
Daubechies	33.6108	28.314	5.3211	63.8403	121.89	7.43	
Symlet	33.5692	28.5864	5.3466	63.803	124.0667	7.4248	
Haar	34.7943	21.5602	4.6433	73.4038	135.7681	7.5319	GDM
Daubechies	34.3782	23.7282	4.8712	73.4146	135.752	7.4496	
Symlet	34.5592	22.7595	4.7707	73.3531	135.7031	7.5122	

As per the results of the Table 3.1 and Table 3.2, the values shows only feeble difference between the normal and the placenta complicated by GDM and also between the Wavelets. At the higher gestational ages as referred in Table 3.3 and Table 3.4, there is a distinct demarcation between normal and GDM complication placenta images. Of all these wavelets, Haar shows a remarkable distinction between these features.

The performance of wavelet decomposition of placenta images taken at 15 weeks of gestational Age is shown in Table 3.3.This gives the metrics that is used to evaluate the normal and GDM Ultrasound placenta.

Table 3.3 Quality Evaluation Metrics to evaluate the performance of Wavelets on normal vs. GDM Ultrasound placenta at 15 weeks of Gestational Age

Wavelet	PSNR	MSE	RMSE	STD	MEAN	Entropy	Class
Haar	34.2999	24.1594	4.9152	34.3881	52.8156	6.5333	Normal
Daubechies	34.0404	25.647	5.0643	34.415	52.9848	6.5404	
Symlet	34.1473	25.0236	5.0024	34.3965	52.7567	6.5357	
Haar	35.6885	17.5481	4.189	32.974	52.3329	6.8749	GDM
Daubechies	35.167	19.7872	4.4483	34.9113	51.5043	6.8435	
Symlet	34.8374	21.3474	4.6203	34.9392	51.4704	6.8632	

The placenta complicated by GDM records higher values when compared to normal. This is clearly indicated in Tables 3.2, 3.3, 3.4 and 3.5.

Table 3.4 Quality Evaluation Metrics to evaluate the performance of Wavelets on normal vs. GDM Ultrasound placenta at 17 weeks of Gestational Age

Wavelet	PSNR	MSE	RMSE	STD	MEAN	Entropy	Class
Haar	36.33	15.1383	3.8908	22.5818	45.9544	6.0968	Normal
Daubechies	35.8815	16.7853	4.097	24.6532	55.2264	6.0799	
Symlet	36.115	15.9067	3.9883	24.6608	55.0351	6.0962	
Haar	36.6246	14.1456	3.7611	24.6962	55.074	6.4061	GDM
Daubechies	36.1327	15.8419	3.9802	22.5477	46.0005	6.4017	
Symlet	36.3917	14.9249	3.8633	22.4784	46.2704	6.4053	

Table 3.5 Quality Evaluation Metrics to evaluate the performance of Wavelets on normal vs. GDM Ultrasound placenta greater than 20 weeks of Gestational Age

Wavelet	PSNR	MSE	RMSE	STD	MEAN	Entropy	Class
Haar	37.0174	12.9222	3.5948	62.3357	93.3318	6.5345	Normal
Daubechies	35.895	16.7333	4.0906	62.3794	94.6397	6.6267	
Symlet	35.5165	18.2571	4.2728	62.4018	94.7556	6.6428	
Haar	40.2942	6.0766	2.4651	59.9116	94.1953	6.5826	GDM
Daubechies	39.7736	6.8505	2.6173	59.918	94.2794	6.5709	
Symlet	38.8101	8.5521	2.9244	60.005	94.0674	6.6186	

It is clear from the numbers in Table 3.1 and that the image obtained from Haar Wavelet decomposition performs better than the Daubechies and Symlet decomposition. However, the quality of the input image remains the same irrespective of the decomposition techniques. The high entropy is the indication of the good quality of the image. From the values in Table 3.6 it can be seen that the wavelet decomposition using Haar dominated the Daubechies and Symlet as indicated by high PSNR of multiview image.

Table 3.6 suggests that at the higher level of decomposition Haar wavelet gives best results. As the decomposition levels increase the performance of Daubechies and Symlet also increase. It has more or less showed similar results at the first level of decomposition. The entropy of the image considerably increased as the levels improved as in Table 3.7. At the highest level of decomposition Haar performs better that the other wavelets.

Table 3.6 PSNR of the different wavelet fused Image at various decomposition levels

Levels of Decomposition	Haar	Daubechies	Symlet
Level 1	34.4689	33.4174	33.2889
Level 2	36.6246	35.8815	35.6885
Level 3	39.7736	37.0174	36.1357
Level 4	40.3112	39.8702	38.8101

Table 3.7 Entropy of the different wavelet fused Image at various decomposition levels

Levels of Decomposition	Haar	Daubechies	Symlet
Level 1	6.0799	6.0594	6.0321
Level 2	6.5709	6.4017	6.6267
Level 3	6.6428	6.4674	6.4016
Level 4	7.4491	6.5709	6.5345

The results clearly imply that Haar Wavelet yields good quality image at the higher levels of decomposition.

3.5 CONCLUSION

Wavelet transform fusion has wide applications and best performance. However, different wavelet basis functions produce different performance. But, the same wavelet basis function performance varies with different decomposition level. The mutual information obtained using Haar

Wavelet decomposition has comparatively better performance than the mutual information obtained using db2 (Daubechies) and sym (Symlet) wavelets. The entropy of the image decomposed at higher levels has greater value. Both these parameters suggest that the decomposed image has more diagnostic information content than the input images. The Haar wavelet decomposition seems to be more efficient than the Daubechies and Symlet in the case of ultrasound placenta images.