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Wavelet Transform for Image Compression Using Multi-Resolution Analytics: Application to Wireless Sensors Data

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Abstract

The aggregation of data in recent years has been expanding at an exponential rate. There are various data generating sources that are responsible for such a tremendous data growth rate. Some of the data origins include data from the various social media, footages from video cameras, wireless and wired sensor network measurements, data from the stock markets and other financial transaction data, super-market transaction data and so on. The aforementioned data may be high dimensional and big in Volume, Value, Velocity, Variety, and Veracity. Hence one of the crucial challenges is the storage, processing and extraction of relevant information from the data. In the special case of image data, the technique of image compressions may be employed in reducing the dimension and volume of the data to ensure it is convenient for processing and analysis. In this work, we examine a proof-of-concept multi-resolution analytics that uses wavelet transforms, that is one popular mathematical and analytical framework employed in signal processing and representations, and we study its applications to the area of compressing image data in wireless sensor networks. The proposed approach consists of the applications of wavelet transforms, threshold detections, quantization data encoding and ultimately apply the inverse transforms. The work specifically focuses on multi-resolution analysis with wavelet transforms by comparing 3 wavelets at the 5 decomposition levels. Simulation results are provided to demonstrate the effectiveness of the methodology.

Keywords

Wavelets, Multi-Resolution Analysis, Image Compressions, Wireless Sensor Networks, Mathematical Data Analytics

1. Introduction

High dimensional image data consist of huge pixels of information that requires large storage space and significantly broad bandwidth resources for data transmissions. Storing and analyzing such data is expensive and the expenses increase as the size of data grows. It is a fact that there are noteworthy advancements in storage technologies and processing functionalities, but the technological advances are not fully able to efficiently handle the volumes, variation, varieties, values and velocities of the huge amount of data. This calls for the need to explore efficient image compression techniques that can store only the relevant information that is needed for reconstruction of the image. In essence, all image data are merely matrices of pixel values and the inherent redundancies should be exploited in compressing every image.

A Wavelet (little wave) is a function that has high time and frequency concentration about a given point. In comparing wavelets with Fourier Transforms (FT), the latter have the shortcoming of addressing simply the frequency components of the signals. That is, temporal information is usually unavailable. Due to Heisenberg's uncertainty principle, we may either have poor frequency resolution and better time resolution or high frequency resolution and poor temporal resolution. Wavelet transforms are mostly useful for non-stationary signals and their basis function varies in both frequency and spatial ranges. Wavelet transforms are implemented in such a manner as to obtain high frequency resolutions at the low frequency portions and good temporal resolutions at the high frequency portions of the signals.

Image compression methodologies are widely used in converting data from big and sparse formats into a more compact and dense format. These mathematical algorithms are classified into the following: Lossless compression approaches and the lossy compression techniques. In the lossy compression methods, compression of images generally comes with data loss or with an associated level of deterioration while retaining the crucial attributes of the images. For the lossless algorithms, it is guaranteed that the data being compressed has a high similarity with the initial data given. This contrast is highly crucial since lossless methodologies are not as efficient at compression as their lossy counterparts. Large data like a huge volume of image data that requires storage, processing and transmission over a network provides a viable example of the advantages of data compressions. This is because the major aim of image compressions is how to obtain the optimum image quality with very small mathematical computation, data transmission and reduced storage costs.

In this work, we examine multi-resolution analysis using wavelet transforms and this is one of the major mathematical and analytical frameworks employed in signal processing and representations, and we study its applications to the area of compressing image data in wireless sensor networks. The proposed approach consists of the applications of wavelet transforms, threshold detections, quantization data encoding and ultimately apply the inverse transforms. The contribution of this work is that it specifically focuses on multi-resolution analysis with wavelet transforms by comparing 3 wavelets at the 5 decomposition levels. Simulation results are provided to demonstrate the effectiveness of the methodology.

2. Review of Related Studies

The body of knowledge is replete with research studies focusing on the application of Wavelet transform to the field of image compression. Researchers have explored different algorithmic frameworks for image compression such as 3-D wavelet transform, linear quantization, one-dimension address complexity, variable length block-coding, adaptive arithmetic with entropy code and so on. The work in [1] explored the compression of biomedical image data [2] using a methodology that is grounded upon a dissociable non-homogeneous 3-D wavelet transforms. It is applied to compress image data from magnet-based resonance imaging (MRI) as well as the compute-tomographic (CT) scan and the results are based on 12 various MRI and CT image data with varying slice thickness. The optimal performance was observed from applying the Haar wavelet transform save for instances of the image data from the CT scans with 1 mm slice-distance. In contrast with 2-D wavelet compression, the percentage of compression employing 3-D approaches is roughly 30% higher in MRI image data and 70% more in CT image data.

In a slightly different perspective, researchers have utilized variable size block coding in representing the cluster of zeros, in conjunction with data decomposition techniques for image compression. A simple but efficient mathematical tool for compressing image data with the aid of a multi-level dyadic wavelet decomposition technique is found in [3]. The rate distortions performance of the proposed algorithm is identical to that of the earlier image data compression technique. The results successfully compressed the Lena and Barbara Images. Wavelet transform has previously found application in wireless sensor networks with energy efficiency constraints. One such application is presented in [4] and it provided an effectively adaptable wavelet image data compression algorithmic framework. It has particular application to the substantial energy minimization required for wireless image data communication while fulfilling the limited bandwidth resource constraints of the associated wireless communication network and the required image quality. This equally provides a significant decrease in the required computation energy, optimizes the network lifetime, lowers the memory requirement and reduces the computational time needed for image compression.

It is possible to explore the crucial features of wavelets transform in the compression of still image data forms and this may include the degree to which the quality of the image data has been compromised through the processes of wavelet compression and decompressions [5]. The coding of image data by wavelet techniques prefers smooth functions with shorter-support and a certain degree of uniformity. The optimum level of decomposition should be arrived at through the image data quality and lowered mathematical computation operation in the process of reconstructing the images. The optimum wavelet functions for some specific image compression application might require modifications in the typical contents of the images [5]. The effects of various wavelets function, image contents and the compression ratios can therefore be assessed. The results in [3]-[9] present a relevant point of reference to application developers in the selection of efficient wavelets compressions systems when designing, developing and implementing user-specific applications.

An exhaustive presentation regarding the usage of wavelet transform for image data compressions is provided in [10]. The research work examined how to utilize wavelet transform for image data compression and provided the underlying theories of wavelet decompositions and its application to image data compressions. Image compression can be efficiently achieved using wavelet transform, multi-resolution analytics, coding and quantization of different scaled-wavelet coefficient. It has been demonstrated that in low energy loss scenarios, threshold compression algorithms provides the highest compression rate [10] [11] [12] [13] [14]. However, this paper focuses on multi-resolution analysis with wavelet transform by comparing 3 wavelets at the 5 decomposition levels. The work has the potential to help the research community in understanding and identifying what first generation wavelet is suitable for which application?

3. Image Compression with Wavelet for Wireless Sensor Data

This research work will particularly focus on the 1st generation of wavelets. The 1st generation wavelets are the classes of important wavelet invented around the 1980s. The basis function of such wavelets is dyadically scalable with respect to the translation property of one unique mother-wavelet basis function. A major drawback of such wavelets is that they are deployable for infinite or periodic signals but they cannot be optimized in bounded regions or domains. The wavelets are typically employed in detecting self-similarity, compressing images, denoising signals, and detecting discontinuity [15] [16] [17] [18] [19]. Some popular types of 1st generation wavelets include:

- Meyer wavelet,
- Coiflet Wavelet,
- Haar Wavelet and
- Daubechies Wavelet.

Table 1 provides a comparison among the various wavelet generations according to their fields of application and dissimilarity.

3.1. Decompositions and Reconstructions

The analytics in our study begins from mother wavelets like the Haars, Daubechies and Morlets [17] [18]. The corresponding signals are then transformed

Table 1. Generations of wavelets, dissimilarity and application.

S/N	Wavelet Generations	Differences	Applications
1	First Generations	These wavelets can be used for periodic or infinite signals but they cannot be optimized in bounded domains	This wavelet transform is used in self-similarity detection, image compressions, signal de-noising, identification of pure frequencies and detection of discontinuities. Other applications are: Acoustic signal compressions, in fingerprint image compression, image processing, enhancement and restoration. Fractal analysis and de-noising noisy data.
2	Second Generations	Fastest for moderately short-filters but one needs to first find the factorizations of the filter banks matrices, but these factors are very well documented for JPEG2000 wavelets.	They are used tremendously for efficient coding in compressions algorithms, computer graphics, geographical data analysis and lossy data compressions. The FBI has used the CDF wavelets in fingerprint compression scans. With these wavelets, compressions ratios of about 20 to 1 could be achieved. They have been applied in multi-resolution analysis, system identifications, and parameter estimations.
3	Third Generations	They do not oscillate and do not show aliasing and degrees of shift variance in their magnitudes. They exhibit a 2D attribute of the signal to be transformed and produce redundancies	They are applied in sparse-representation, multi-resolution and useful features characterizations based on the image structures. They are also used in medical profession because they provide intuitive bridges between time and frequency data that could clarify interpretations of complex head-trauma spectra produced with Fourier transform. They are also used in music industry for transcriptions of music since they produced precise results that were not possible earlier with the Fourier transforms. It is capable of capturing short-bursts of repeating and alternating music notes.
4	Next Generations	They will be too specific and too constrained because These wavelet transforms are still very much at the research stage and meant for specific applications	The applications will include human-vision characterizations, frequency localizations, feature extractions, analysis of seismic information, analysis of biomedical information, wireless sensor networks [17] [18] [20] [21] [22] [23] etcetera.

unto scaled and shifted versions of the given mother wavelets. Wavelet decomposition analytics is employed in dividing information of the image data into the approximations and detail sub-signals. Approximation sub-signals usually display the overall trends in the pixels and the associated values as well as the three details sub-signal each from the vertical, diagonal and horizontal detail of the signals. The details could be equated to zero provided they are negligible, without substantial changes in the image data. Hence, when signals are decomposed into their corresponding sub-signals, four images are obtained, the first are the approximate images and the remaining three correspond to the diagonal details, horizontal details and vertical details as **Figure 1** depicts.

Inverse technique to decomposition operation is called signal reconstruction operation. The overall decompositions and reconstructions are provided in **Figure 2**. Whenever signals are sent through the low-pass filters (LPF) and the high-pass filters (HPF), the signals are generally decomposed to two components —a detail portion (High-frequency parts) and an approximate portion (Low-Frequency components). The sub-signals generated from the LPF would have a largest frequency that is equal to one-half of the original signal frequency. With respect to the Nyquist-sampling criterion, these frequency-range changes imply that just half the original signal samples should be preserved to guarantee a perfect reconstruction of the original signals. At each level of four sub-images, there

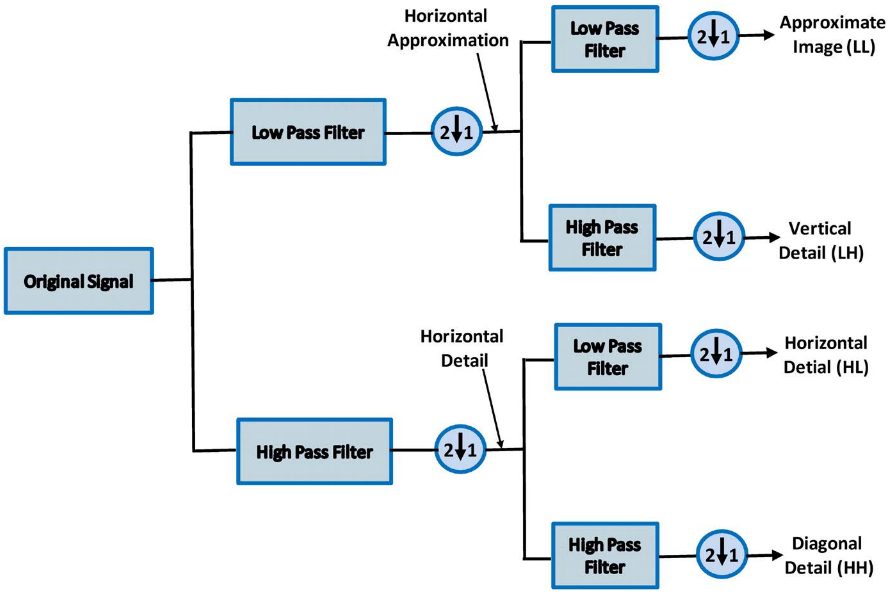

Figure 1. Image data or signal decompositions using wavelets transform.

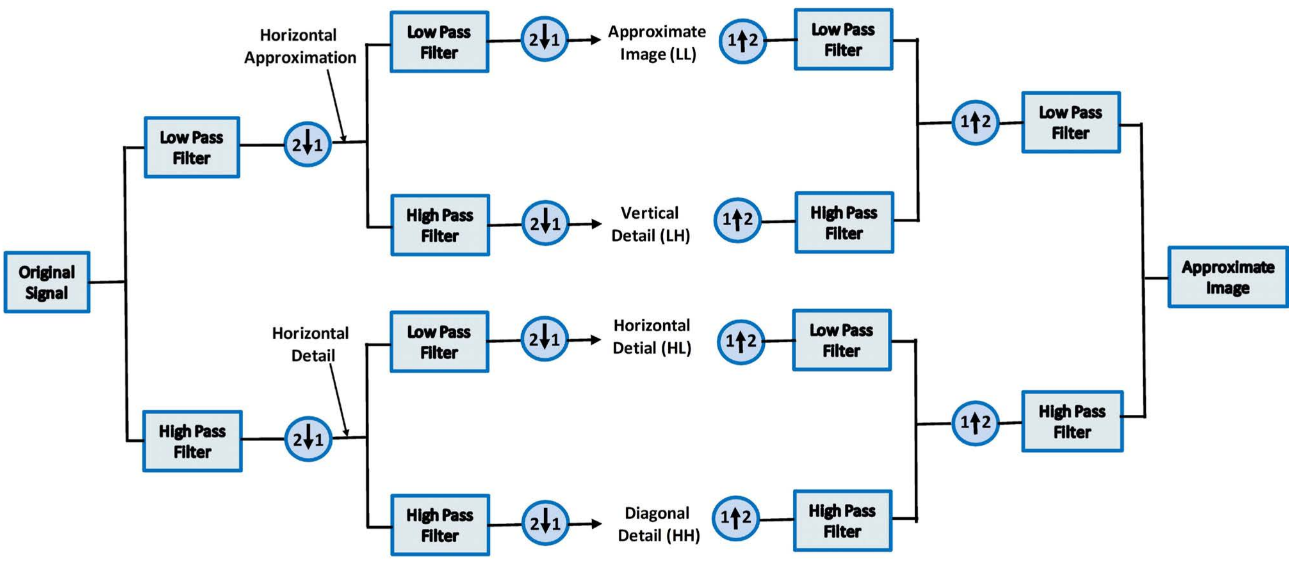

Figure 2. Data, image or signal decomposition and reconstruction.

will be one approximate detail followed by three detailed sub-signals on the diagonal, vertical and horizontal details. The wavelet reconstruction computation should generate approximate images identical to the original image signals.

3.2. Sensor Data Compressions with Wavelet Analytics

The remaining sections detailed how we employed wavelet analytics for image data compression. The following provides the general steps utilized in the data compression processes.

The compression methodology employed in this work exploits the wavelets expansion of sensor data and retains the maximal absolute-value-coefficients. Thus, we could choose some global thresholds or certain compression performance-metrics or a relative-squared-norm recovery performance metrics and it only requires the selection of a unit parameter. We load the sensor data and observe the compression performance for a selection of any un-optimized wavelets so as to have a total squared-norm recovery of the loaded sensor data. Finally, global threshold is implemented and the idea is to use multi-resolution analysis with wavelet transforms to compare 3 wavelets at the 5 decomposition levels. This has the potential to help the research community in understanding and identifying what wavelet is suitable for which application?

The compression attributes of any choice of wavelet basis are typically related to the relative scarcity of wavelet domain representation of the signals or data. The main idea associated with compression is hinged upon the fact that regular signal component might be accurately approximated by using the following: Very small amount of the approximation coefficients (at suitably selected level) and few of the detailed coefficient. The analysis is concluded by including the values of perf0 and perfl2 in the MATLAB codes for decompositions.

Decompositions: This entails how to load the data or images, selecting the appropriate wavelets, selecting a decomposition level N, computation of the wavelet decomposition for the data fat that chosen level N.

Threshold the details coefficients: It entails selection of the appropriate threshold and the application of hard thresholding to the details coefficients for every level in 1 to N.

Reconstructions: The computation of the wavelets synthesis is completed by using the originally obtained approximation coefficient for level N as well as the modified detailed coefficients for levels 1 - N.

4. Simulation Results

In order to evaluate the difference between the original and compressed images, we used the following performance metrics: % root-mean-square difference (PRD), the compression ratio (CR) and the quality factor (QF).

Let X represent the original image and Y, the reconstructed image, the PRD is expressed as:

$$PRD = \sqrt{\frac{\sum_N [X - Y]^2}{\sum_N X^2}} \times 100\% \tag{1}$$

CR is the ratio of the uncompressed image size to the compressed image size and it is expressed as:

$$CR = \frac{\text{Uncompressed Image Size}}{\text{Compressed Image Size}} \tag{2}$$

While the QF is the ratio of the square of the CR to the PRD and it is expressed as:

$$QF = \frac{CR^2}{PRD} \tag{3}$$

The integrity of the decomposition process relies heavily on the choice of wavelet. Thus, we examine the choice, among three wavelets, for the most appropriate mother wavelet for signal compression. The three wavelets are Haar wavelet, Daubechies type 4 and type 8 wavelets (DB4 and DB8). The data is loaded to the algorithmic framework sequentially and the compressions ratio of 50:1 is observed. The L2 norm recovery percent is 99.261% and the Compression-score percent is 97.993%. We then quantified the PRD, CR and QF of the compressed signal. The simulation results are shown in **Figures 3-5** from which it is observed that the decomposition level as well as the choice of mother wavelet affects the PRD, CR and QF of the compressed signal. In **Figure 3**, the percentage root-mean square for DB-4 is similar to that of DB-8 while the PRD of Haar is higher than that of the DB-4 and DB-8 for all decomposition levels. **Figure 4** and **Figure 5** show that the compression ratio and the quality factor of the Haar wavelet is higher than that of both the DB-4 and DB-8 and DB-8 has the lowest compression ratio and quality factor for all decomposition levels. We found that within the first generation wavelets that we used, the Daubechies-4 type of wavelets performed better since it has the least percentage root-mean square difference and better compression ratio and quality factor than the DB-8.

5. Conclusion

The paper investigated image compressions using the 1st generation wavelets transforms. Based on reviewing the recent wavelet-based image compression algorithmic frameworks, various challenges are identified which include: The in-

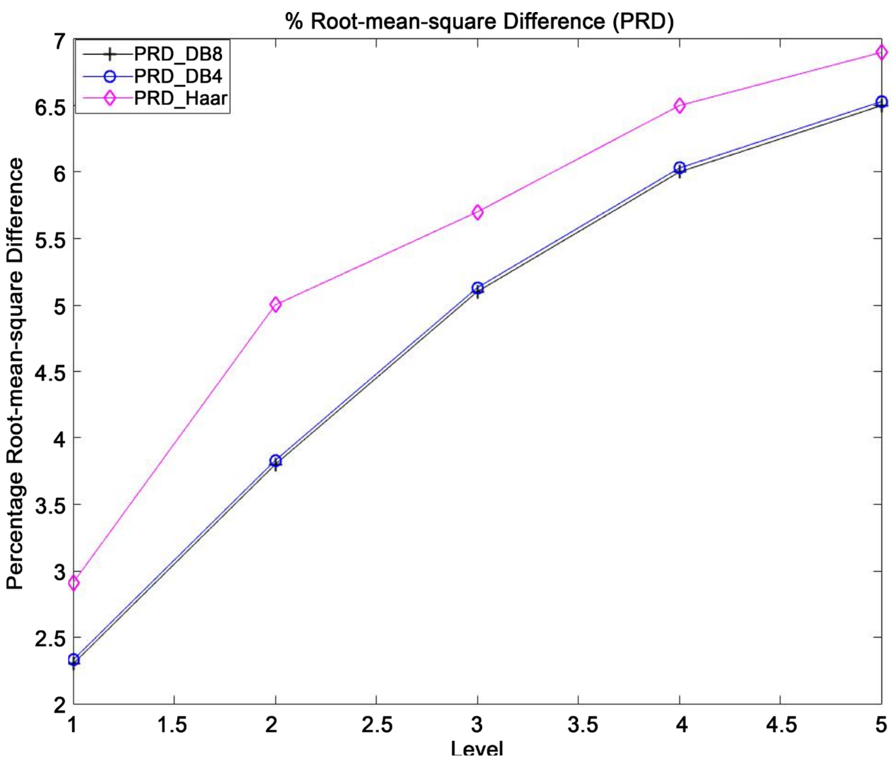

Figure 3. Percentage Root-mean-square difference in relation to the decomposition level and the mother wavelet used.

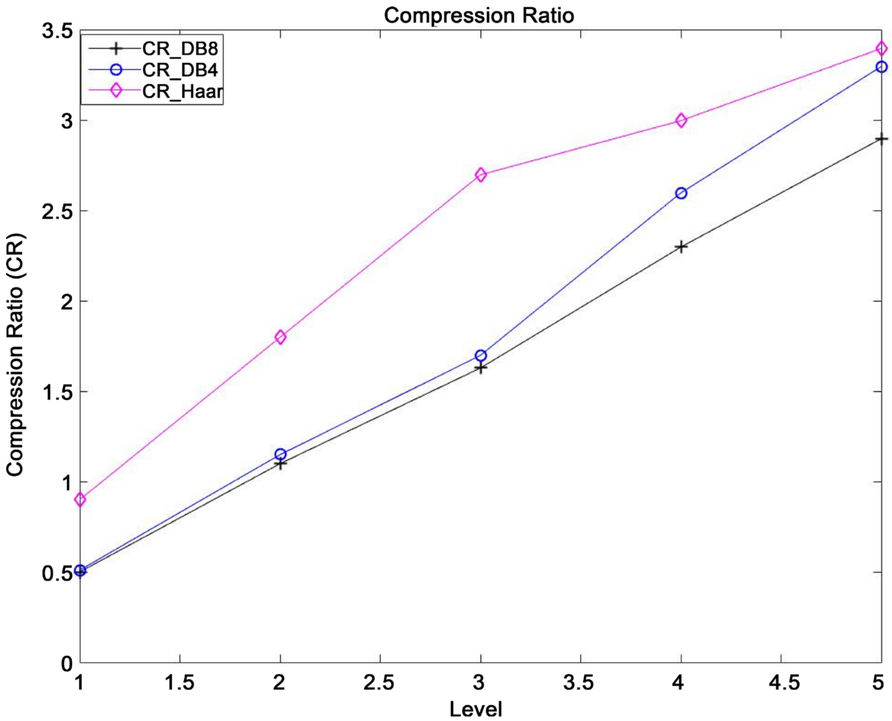

Figure 4. Compression ratio in relation to the decomposition level and the mother wavelet used.

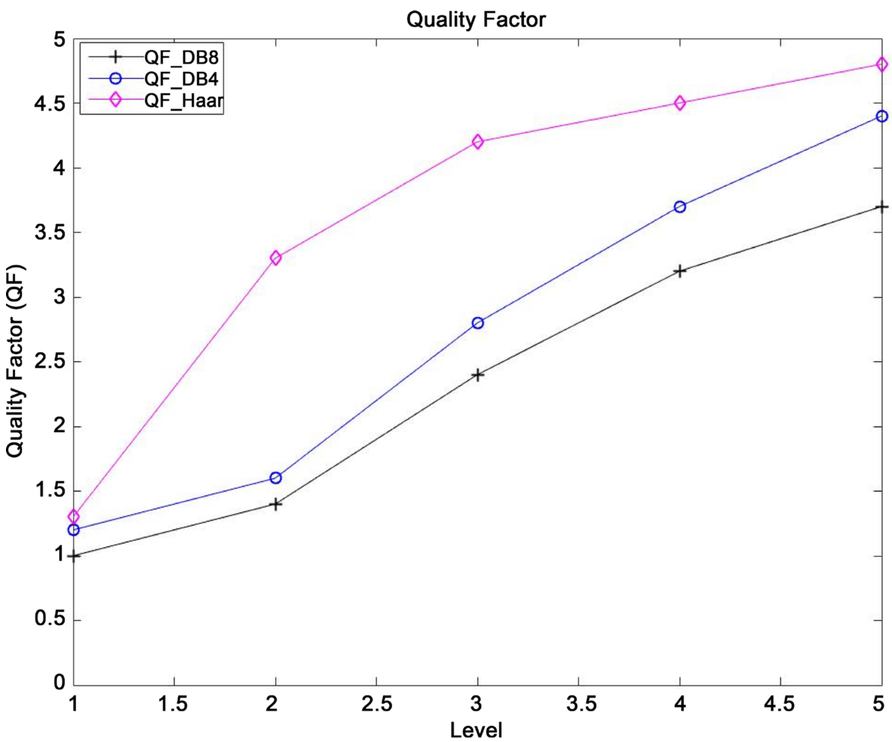

Figure 5. Quality factor in relation to the decomposition level and the mother wavelet used.

herent challenges linked with the high-complexity of data-encoding process of current algorithmic frameworks. Many of the modern methodologies need the developer to generate codebooks or lookup table that engulfs more implementation or computation cost. Better data quality and better compression ratios can be obtained by employing some other more compression-efficient wavelet transforms like the standardized CDF 9/7 utilized in fingerprint compressions. In this work, we found that within the first generation wavelets that we used, the Daubechies-4 type of wavelets performed better. In our future work, we will explore other types of wavelets and compare with the ones we used in this research study.

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