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HYBRID AUDIO COMPRESSION USING FRACTAL CODING AND WAVELET TRANSFORM

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ABSTRACT

Fractal audio compression (FAC) is based on the concept of partitioning audio data, and then exploiting the self-similarity present in audio signal in order to eliminate the redundancy may exist in audio signal. This elimination plays a significant role in audio compression. The key step for fractal coding is to pick up the domain blocks which are similar to the original blocks (i.e., range blocks), and these range blocks are represented as a set of affine transformations [1]. Fractal compression has a significant draw back especially while coding large range blocks since the level of error produced is very high and unaccepted. In order to improve performance in terms of compression gain and fidelity error of the fractal coding especially in case of using long range blocks, the wavelet method is utilized. The tests results indicate that a significant improvement in the PSNR values occurs; making a significant decrease in the compression error level after the addition of wavelet method. Moreover, the attained results of the conducted tests when using the wavelet transform for multiple passes and rounds implies a significant increase in the compression ratio values as the block length increase, while the generated PSNR carries good and acceptable values which reaches 30db.

Keywords: fractal audio compression, wavelet transform, range blocks, compression error level.

1. INTRODUCTION

In general, there are many known strategies for compression which primarily based on special ideas that are suitable for different forms of data and produce distinctive outcomes. However, they may be all based totally on the similar principles which are extracting redundancy from the original information within the source file. In fractal audio compression method, the domain pool is a collection of down sampled sub sound where the transformation maps from, and the 'range' is the region where the transform maps to. The most valuable advantage of fractal coding is the ability to achieve high compression ratios, and this is achieved since Fractal encoding is essentially a process to find close mappings, or transformations if affine is required, for each range block from the domain blocks. We only need to store the domain location and the coefficients of each transform after encoding. Quite a lot of bits can then be saved over the original data.

But fractal compression has not been put into practical use for its weaknesses. The success of the scheme seems to rely exclusively on exhibiting some self-similarities among part of the space. And there is no guarantee that the probability of matching domain and range blocks is sufficiently high to achieve good compression especially in large range blocks which leads to high increase in the compression error level. To overcome this weakness the wavelet transform method is utilized. Wavelet transform is applied on the produced error for several passes; the effect of wavelet in this research shows a high increase in PSNR for different values of large block lengths which leads to high reduction in error level.

2. LITERATURE REVIEW

In 2005, Henry Xiao explored the overall performance of utilizing fractal coding on audio data in his thesis. Additionally, he had studied a few traditional fractal coding problems to provide a top-level view about the issue. He determined that fractal coding is not particular sufficient to handle all audio compression demands. Moreover, he determined that the compression ratio from utilizing fractal audio coding can be in a range from 3 to 6 [2]. In 2006, George, explored a new fractal image coding scheme based totally on IFS-transform for zero mean range-area blocks. He had made some upgrades on the IFS-matching level through using moments primarily based indexing as a way to pick the set of area blocks which are suitable to suit every variety block individually. additionally, he used a stopping search condition based totally on tracking the minimal matching error, as a reason to reduce the long fractal coding time (round 3.5 times) [3]. In 2009, Wannamaker and Vrscay introduced a unique method to audio signal compression that is a mixed scheme based totally on each wavelet transform and fractal coding. They divided the signal into frames, in which each one is subjected to a fast wavelet transform followed via fractal coding for high frequency wavelet coefficients using collage based technique [4]. In 2011, George and Eman brought a fast image compression method; they make use of moment functions extracted from the zero-mean range blocks and a new symmetry prediction criterion is used to decrease the number of isometric trails from 8 to 1 trail. Moments had been utilized to speed up the iterated function systems (IFS) matching level. These functions had been used to find out the block descriptor "moment ratio index", which is applied to classify the image blocks in both domain and range pools all through the encoding level. The block moment ratio descriptor of every range blocks is used to scan the area blocks and pick only the blocks whose descriptor is suitable to be IFS matched with the examined range block [5].

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3. THE PROPOSED APPROACH

This research work is dedicated to introduce a trial to improve a hybrid system model consist of mixed traditional fractal compression with Wavelet transform method. A new way of decreasing the compression error gain is introduced; by applying wavelet technique for more than one round and pass for large blocks.

3.1 System model

3.1.1 Discrete wavelet transform (DWT)

The discrete wavelet transform (DWT) is considered as one of the highly flexible family of signal representations that it is matched to a given signal, and it is well viable to the task of audio data compression [6]. Wavelet coding is based on the concept that the coefficients of a transform decorrelates the values of an audio signal sample and can be efficiently coded more than the original samples themselves. Most of the significant part of the information is represented by a smaller number of coefficients, while the remaining coefficients can be quantized or truncated to zero with few distortions in perception of coded audio signal.

In the DWT, a signal is analyzed by passing it through a filter bank followed by a decimation operation. The analysis filter bank consists of a high pass and a low pass filter at each decomposition stage. When the signal passes through these analysis filters, it splits into two bands. The low pass filter that corresponds to an averaging operation, which extracts the coarse information of the audio signal. The high pass filter that corresponds to a differencing operation, which extracts the detail information of the audio signal. Then the output of the filtering operations is decimated by two [7]. The (DWT) is designed by successive high-pass and low-pass filtering of the discrete time domain signal as represented in Figure-1. In the corresponded figure, the sequence (x[n]) denotes input signal, where (n) is an integer. The low pass filter is given by (G_0), while the high pass filter is given by (H_0). At each level of decomposition, the coarse approximations a[n] is produced by the low pass filter, while the detail information d[n] of the signal is produced by the high pass filter. The filter banks used in forward wavelet transform is called analysis filters and the filter banks used in inverse wavelet transform is called synthesis filters.

Various architectures are used for implementing a filter bank; i.e. direct form, Polyphase, Lifting Scheme and Lattice structure. Basically, a filter bank consists of a high pass filter and a low pass filter followed by expanders or decimators and delay elements.

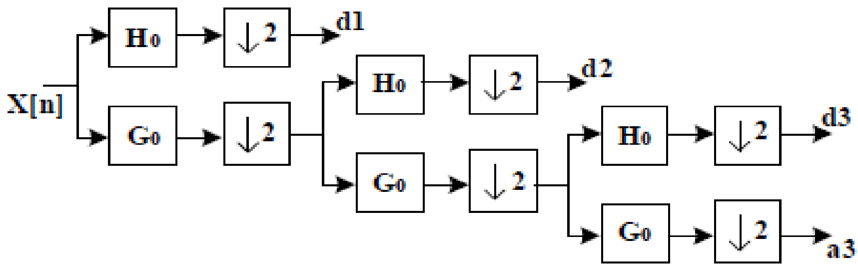

Figure-1. Level decomposition DWT.

3.1.2 Lifting scheme for DWT

Lifting scheme an effective way to design a DWT. Accumulator and complex multiplier units used in FIR filters as shown in Figure-2; are designed by using a simple prediction technique. The FIR filters consist of three steps: split, predict and update. The Lifting scheme is shown in Figure-3.

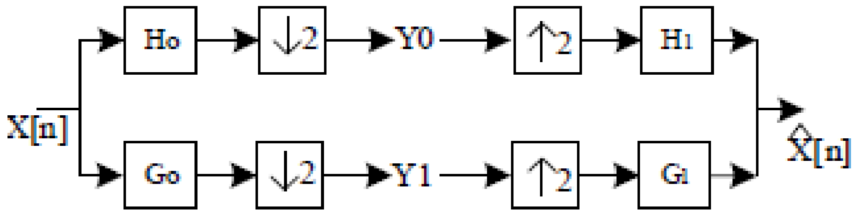

Figure-2. Analysis and synthesis filter banks for DWT.

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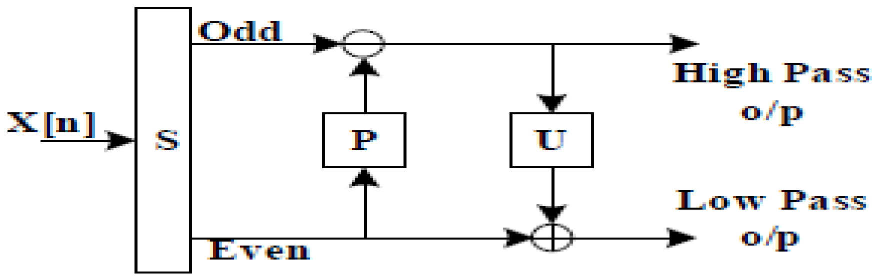

Figure-3. Lifting scheme for DWT.

A. Split

In the split step, the input $(f\ [k])$ is divided into two samples; even (λ[k]) and odd (γ[k]) samples:

$$f\ [k] = \begin{cases} \lambda[k] = f\ [2k] \\ \gamma[k] = f[2k+1] \end{cases} \tag{1}$$

B. Predict

This step uses a function that approximates the odd samples. It is called dual lifting. It gives an interpolation on even samples. The differences between the actual values and the approximation; replace the odd samples of the data set. It provides a high pass filtered component. The odd values is predicted from the even values, which is described by the equation given below:

$$\gamma[k] = \gamma[k] - P\ (\lambda[k]) \tag{2}$$

Where, (λ[k]) is the even sample, (γ[k]) is the odd sample and P() is the prediction function.

C. Update

In this step, scaling is utilized to smooth the data and then added with even samples to provide a low pass filtered values for the DWT. It is called primal lifting. This results in a smoother input for the following step of the wavelet transform represented in the following equation:

$$\lambda[k] = \lambda\ [k] + U\ (\gamma\ [k]) \tag{3}$$

Where, (λ[k]) is the even sample, (γ[k]) is the odd sample and U() is the Update function.

3.1.3 Lifting scheme on biorthogonal (db9/7) WT

Db9/7 lifting scheme have two lifting steps. It consists of 5 operations: Predict1, Update1, Predict2, Update2 and Normalization. While the values of constants are given in Table-1. Figure-4 shows the layout of the proposed fractal system in addition to wavelet.

Predict 1: $Y_{2n+1} = X_{2n+1} + \text{A}\ X_{2n} + X_{2n+2}$ (4)

Update 1: $Y_{2n} = X_{2_n} + \text{B}\ Y_{2n-1} + Y_{2n+1}$ (5)

Predict 2: $Y_{2n+1} = Y_{2_n+1} + \text{C}\ Y_{2n} + Y_{2n+2}$ (6)

Update 2: $Y_{2n} = Y_{2n+1} + \text{D}\ Y_{2n-1} + Y_{2n+1}$ (7)

Normalization 1: $Y_{2n+1} = -K * Y_{2n+1}$ (8)

Normalization 2: $Y_{2n} = (1/K) * Y_{2n}$ (9)

Where, X() is the input array & Y() is the wavelet transform outcome array.

Table-1. Filter coefficients for biorthogonal WT.

Coefficients	Floating Point Value	Coefficients	Floating Point Value
A	-1.586134342	B	-0.052980118
C	-0.882911075	D	-0.443506852
K	1.230174105	1/k	0.812893066

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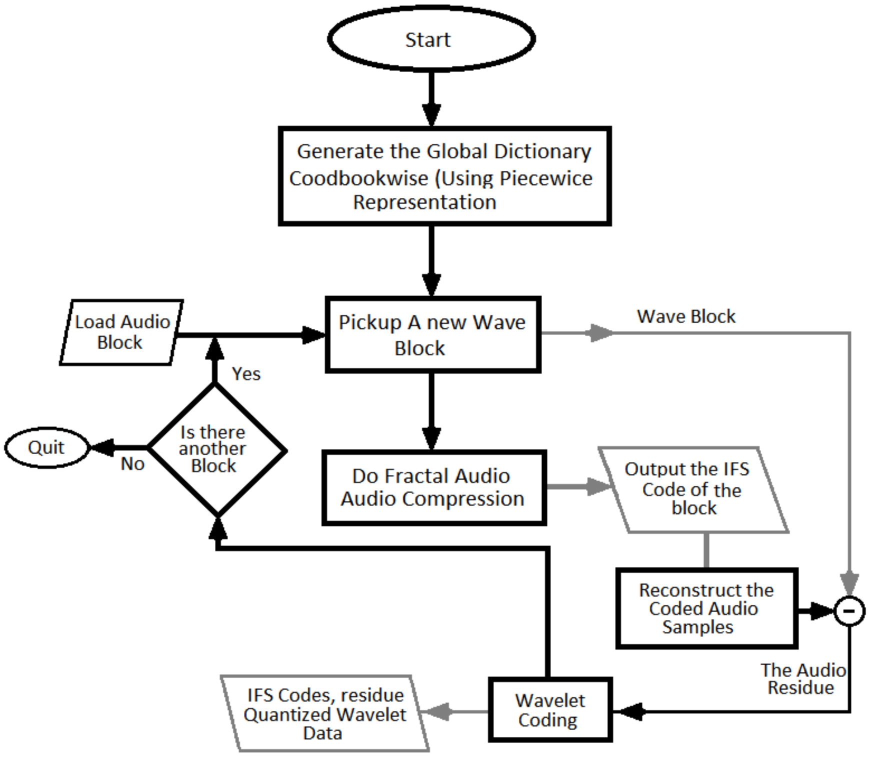

Figure-4. The Layout of proposed fractal system with wavelet addition.

4. TEST RESULTS

This part is dedicated to show the results of the conducted tests to study the effects of wavelet passes on different block length values; large values of block length are utilized in the following tests because of high compression error it consists. The following system performance measures {i.e., compression ratio (CR), peak signal to noise ratio (PSNR), and encoding time (ET)} have been used to assess the performance efficiency of the FAC developed schemes.

Finally, it is essential to mention some information that is related to the SW & HW environment at which the program is developed and executed. The program was constructed using C# visual studio as SW development tool, and the HW environment used during our test is a single PC with Intel (R) Core™ (1.80 GHz), and 4.00 GB RAM. In the conducted tests; the four audio samples of size 303 KB (sample 1), 140 KB (sample 2), 393 KB (sample 3) and 375KB (sample 4) have been adopted as test materials. Tables (2 - 7) show the comparison between different wavelet passes on different fixed block length values. Figures (6 and 8) show the relation between CR and PSNR as the number of passes increase for three different fixed values of block length (256, 192, 128) for sample 2 of (bit depth=8, sampling rate=44100) and sample 3 of (bit depth=16, sampling rate=22050); Figures (5 and 7) the relation between CR and PSNR as the number of block length increase for three different fixed values of no. of passes (3, 4, 5) for sample 2 and sample 3.

Table-2. Comparison of PSNR and CR values between the different wavelet passes of block length 256.

Tested Samples	Fractal approach without wavelet		Fractal approach with wavelet (3 passes)		Fractal approach with wavelet (4 passes)		Fractal approach with wavelet (5 passes)	
	PSNR (db)	CR	PSNR (db)	CR	PSNR (db)	CR	PSNR (db)	CR
Sample 1	29.31	178.0	45.84	8.696	40.049	16.58	30.879	30.34
Sample 2	20.19	85.33	43.69	4.338	39.101	8.258	30.264	15.05
Sample 3	19.29	178.0	49.49	8.696	44.980	16.58	38.175	30.34
Sample 4	20.60	170.6	49.41	8.677	45.276	16.51	38.161	30.11

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Table-3. Comparison of ET values between the different wavelet passes of block length 256.

Tested Samples	Fractal approach without wavelet	Fractal approach with wavelet (3 passes)	Fractal approach with wavelet (4 passes)	Fractal approach with wavelet (5 passes)
	ET (sec)	ET (sec)	ET (sec)	ET (sec)
Sample 1	2.25	2.50	2.25	2.35
Sample 2	4.14	4.18	4.14	4.15
Sample 3	2.80	2.79	2.80	2.81
Sample 4	5.71	5.65	5.71	5.70

Table-4. Comparison of PSNR and CR values between the different wavelet passes of block length 192.

Tested Samples	Fractal approach without wavelet		Fractal approach with wavelet (3 passes)		Fractal approach with wavelet (4 passes)		Fractal approach with wavelet (5 passes)	
	PSNR (db)	CR	PSNR (db)	CR	PSNR (db)	CR	PSNR (db)	CR
Sample 1	29.34	133.5	43.90	8.55	38.852	16.0	30.120	28.71
Sample 2	20.63	64	41.38	4.26	36.561	8.04	28.076	14.22
Sample 3	19.32	128	41.82	8.53	38.382	16	33.360	28.44
Sample 4	20.65	128	48.04	8.53	43.455	16	36.615	28.44

Table-5. Comparison of ET values between the different wavelet passes of block length 192.

Tested Samples	Fractal approach without wavelet	Fractal approach with wavelet (3 passes)	Fractal approach with wavelet (4 passes)	Fractal approach with wavelet (5 passes)
	ET (sec)	ET (sec)	ET (sec)	ET (sec)
Sample 1	2.29	2.29	2.43	2.28
Sample 2	4.33	4.33	4.49	4.25
Sample 3	2.88	2.88	3.37	2.88
Sample 4	5.37	5.37	5.33	5.35

Table-6. Comparison of PSNR and CR values between the different wavelet passes of block length 128.

Tested Samples	Fractal approach Without wavelet		Fractal approach with wavelet (3 passes)		Fractal approach with wavelet (4 passes)		Fractal approach with wavelet (5 passes)	
	PSNR (db)	CR	PSNR (db)	CR	PSNR (db)	CR	PSNR (db)	CR
Sample 1	29.345	85.3	37.22	8.25	33.437	15.05	27.175	25.6
Sample 2	21.222	40.9	35.01	4.11	31.218	7.474	24.385	12.6
Sample 3	19.238	85.3	36.72	8.25	33.351	15.05	28.441	25.6
Sample 4	20.696	81.9	38.67	8.22	35.311	14.94	30.507	25.2

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Table-7. Comparison of ET values between the different wavelet passes of block length 128.

Tested Samples	Fractal approach Without wavelet	Fractal approach with wavelet (3 passes)	Fractal approach with wavelet (4 passes)	Fractal approach with wavelet (5 passes)
	ET (sec)	ET (sec)	ET (sec)	ET (sec)
Sample 1	2.03	2.03	2.02	2.03
Sample 2	3.62	3.62	3.47	3.46
Sample 3	2.86	2.86	2.83	2.84
Sample 4	4.78	4.78	4.80	4.82

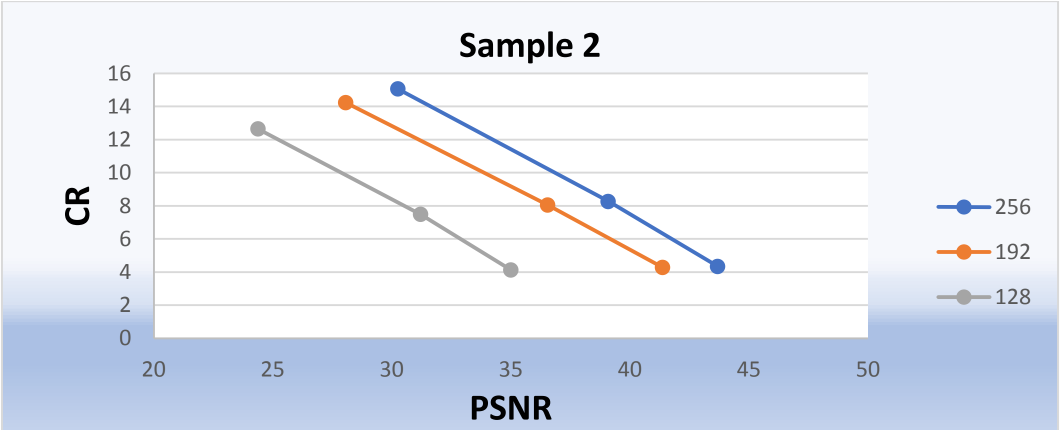

Figure-5. The relation between CR and PSNR as the number of passes increase for three different fixed values of block length (256,192,128) for sample 2 (bitdepth=8, samplingrate=44100).

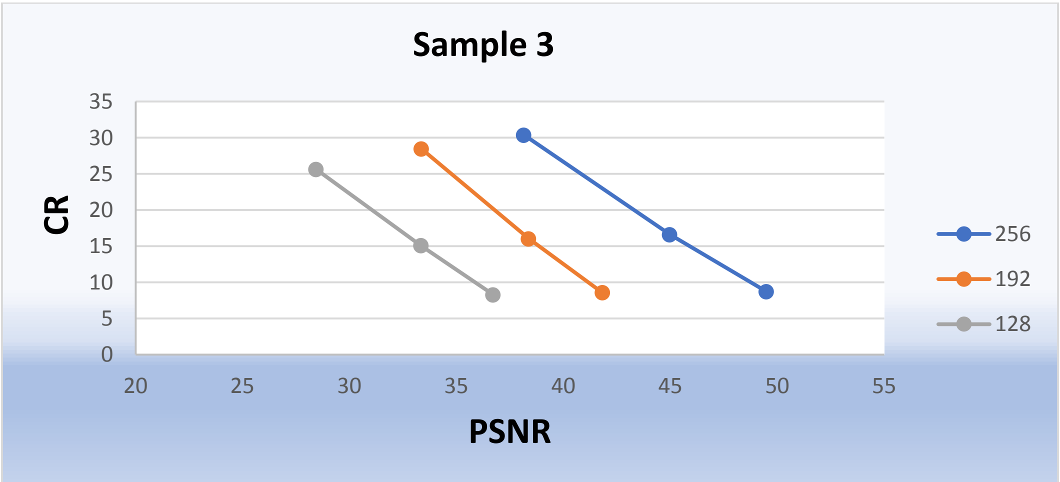

Figure-6. The relation between CR and PSNR as the number of block length increase for three different fixed values of no. of passes (3,4,5) for sample 2 (bitdepth=8,samplingrate=44100).

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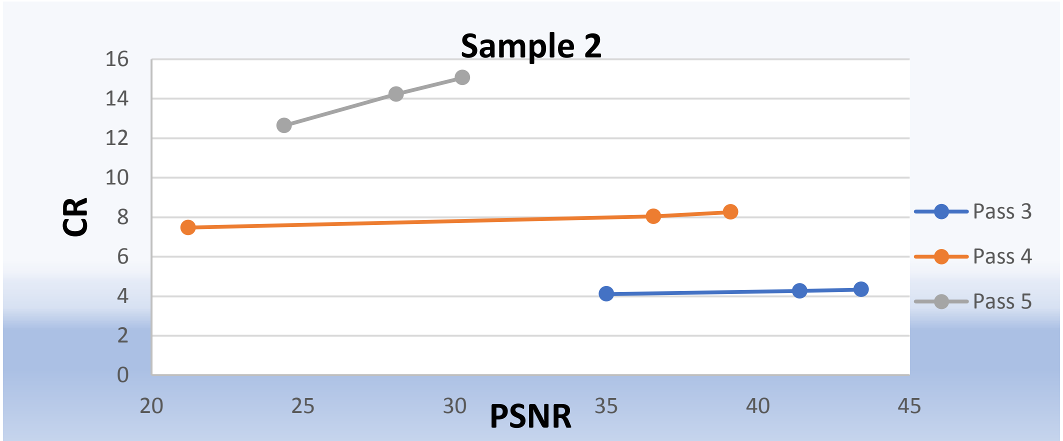

Figure-7. The relation between CR and PSNR as the number of passes increase for three different fixed values of block length (256,192,128) for sample 3 (bitdepth=16, samplingrate=22050).

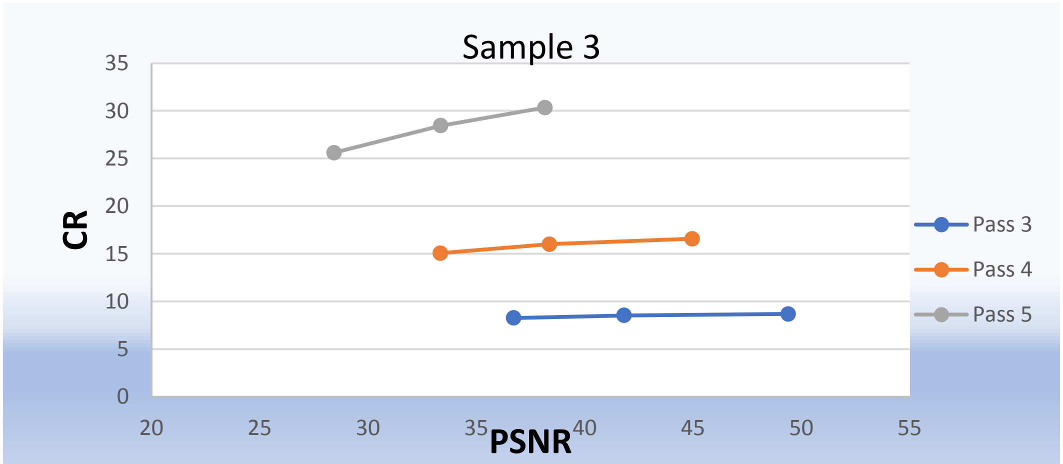

Figure-8. The relation between CR and PSNR as the number of block length increase for three different fixed values of no. of passes (3, 4, 5) for sample 3 (bitdepth=16, samplingrate=22050).

The results of the conducted tests indicate that:

a) PSNR is highly increased with the addition of wavelet.

b) ET minor affected by the wavelet, also slightly affected by the number of passes.

c) CR is decreased under the effect of wavelet addition.

d) As the number of wavelet passes increase the PSNR decreases.

e) As the number of wavelet passes increase the CR is increases.

CONCLUSIONS

The results of the wavelet on the proposed fractal approach show that PSNR is highly increased with the addition of wavelet, but ET is not affected by the wavelet and its number of passes. Moreover, CR is decreased under the effect of wavelet addition. As the number of wavelet passes increase the PSNR decreases. In addition to that, as the number of wavelet passes increase the CR increases too. So the compression error level is effected in a significant way by the wavelet addition; The produced results carries good values of both CR and PSNR; the results are considered good and acceptable.

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