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Error Free Coding In Transformed Domain for Multimedia Streaming

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Abstract

This paper describes a new method for video streaming encoding based on the transformed spectral encoding of video images. In the process of streaming of video frames, the spatial streaming method is more affective the streaming noise. The transformed domain approach minimizes this noise effect, but a better streaming of the information is not accurately interpolated. To achieve a finer streaming streaming is a new method of spectral domain streaming is proposed. A spectral coding for efficient tape applied to achieve higher efficiency machining with machining accuracy. To achieve a better noise elimination is an approach between the frame correlative filtering logic proposed. The proposed methods are evaluated with the conventional streaming logic of spatial and transformed domain, calculate the parameter analysis of PSNR, RRE, the calculation time. An improvement of the proposed strategy is observed in comparison with conventional streaming methods.

Keywords: Error free coding, multimedia streaming, transformed domain.

INTRODUCTION

With the development of new devices for the capture and processing of images, high quality images and videos are produced. Video information is more informative compared to still images. However, the size of these files limits their use for the low restriction environment. To provide a video interface in a low resource environment, video data is transformed into a lower scale to address resource constraints. In the field of image processing there is a need to improve the resource requirements for progressive image processing using resource optimization techniques. In previous approaches it is observed that the sequencing of images can be improved by the optimization of the use of available resources. The lowest scalability provides a feasible use in resource constraints, but the display problem is observed on the receiving side. The lower scale degrades the quality of the video frames compared to their actual high-resolution rendering. Therefore, streaming logic is performed to convert high resolution representation. In order to achieve a higher resolution coding, most of the streaming logic involves the processing of a video frame as two-dimensional data and the application of 2-D image processing techniques to reflect the data. If conventional projection approaches [1] [2] were processed using pixel size, direct streaming would be more error-prone. A Fourier domain coding has been proposed as an energy-based streaming encoding towards [11]. Although Fourier streamings are more accurate when compared to conventional coding in projection, individual resolution coding is not considered. The advantage of multi-resolution analysis coding (MRA) is proposed for energy-based projection. While the multi-resolution projection results in a more accurate projection, the integrated video noise are also predicted, this results in a wider display distortion in the projected video file. The noise reduction approach is focused on a multi-resolution streaming approach to achieve higher streaming accuracy. To present the proposed approach the rest of the paper is presented in 6 sections. Section 2 presents the conventional state of art for streaming of video frames and its filtration during projection. Section 3 outlines the proposed inter frame 3D filtration for video coding. The obtained experimental results for the suggested approaches were presented in section 3. Section 4 presents the conclusion of the presented work.

LITERATURE SURVEY

It has been observed that methods based on the previously proposed super-resolution [1-4] were developed and kept in mind by preserving existing resources. When resource improvements are constrained, coding based on vector reduction techniques [6, 7, 9] is specified to increase the quality of the image processing. To achieve higher visual quality, the specified streaming approaches were implemented using frequency transformation [5, 10] transformation techniques. Although these streaming methods are efficient to produce an HR image from a low LR image, they cannot provide effective visibility. In [11], Fourier domain coding is presented to improve streaming performance to achieve better resolution streaming performance. In this approach of energy-based streaming, a new encoding of multiple spectral coding is presented. However, noise streaming must be removed before the projection is encoded. Possible assumptions made about the nature of the relationship between assumptions can be made implicitly as part of a reconstruction algorithm such as a simple band-limited model [1] or a certain regularity [2] or consist of a predicted model of LR source data. For this latter case, some new examples have various second-order statistical modeling techniques [3,4], both of which relate to a single LR image. The use of a power spectral density (PSD) modeling approach and support vector correction [6] is proposed for the projection approach. Since the exact relationship between the LR and HR sequences is not known, there will be some errors in the estimated sequence video sequence. Previous approaches have been proposed for video-video [8, 9] and video-image problems [10]. The basic solution is a relatively simple block-processing linear minimum mean-squared error (LMMSE) spatial domain streaming. In many ways, the solution is similar to previous approaches for still image scenarios; however, some changes have been made to improve performance and to avoid some of the complications that are particularly apparent for video performance. Most previous approaches contemplate a still image scenario, but most of them do not preclude the video. An overview of the question is found in the research article [7]. The difficulties of the still image problem are discussed in many of the articles cited in this survey and in many of the subsequent studies. For this reason, there may be substantial mismatched parts or contents; this can degrade High-resolution performance if not removed. There are alternatives for block-based recording such as [11] which can provide a better representation of the natural motion in the video sequences. The proposed approach also includes data validation checks to improve the integrity in case of a registry error.HR estimates are computational requirements for estimation, matrix operations in [1] and [2] together with the computation required to estimate the required correlation matrices. Under simpler conditions, the source data is found at even intervals, and the LR grid interval is the integer multiple of the HR grid interval. PSD-based methods in previous methods (e.g., Edge-oriented streaming [3] or [4,5]) have accepted such conditions that a uniform HR correlation function is estimated from the uniformly down sampled equivalent. In the parametric modeling approach [5], the approach for faster block processing has been simplified to estimate the PSD of an image. Correlation is found using the 2D fast Fourier transform (FFT) approach. Assuming an anti-softener degradation between the HR and LR versions of a block, the low frequencies of the HR block can be computed directly as if it corresponded to the entire LR block.[5] And an important observation discussed in previous studies is that the lower frequencies of the spectrum represented by the size of the FFT dominate the higher frequencies with almost always a few magnitudes in standard views. Thus, replicating the HR spectrum of the complex LR spectrum onto the base band increases the great majority of statistical information.

TRANSFORMED DOMAIN CODING

To optimize video encoding under noisy conditions, a common contiguous match and monotone region harmony is used. In the joining process to the adjacent regions, if the time slot t is found as a match and t + 2 matches, then t + 1 is considered a match. If t and t + 2 do not agree with the query in single-domain regions, then t + 1 is also discarded. On the selected histogram region, the dataset histogram feature is compared to obtain the best match information. However, even if the noise effect is not classified under the adjoining region and the single tone region selection, it leads to the least reduction of the acquisition performance. It has been observed that the noise reduction is performed based on the contiguous region process. Sounds distributed over a frame period can be reflected as a video content and are not calculated with such an approach. Therefore, a longer frame analysis is required for the system to be more noise resistant. To remove the Noise Effect from the center, an intra-frame correlation error is considered for a time frame set. Considering a set of Histogram (H_k) for a given video data set of M,

$$H_i(k) = [H_i(kN), H_i(kN-1), \ldots\ldots, H_i(kN-M+1)] \quad (1)$$

Where, H_i is the Histogram for a given video frame, N is number of frame and M are the dataset samples. To evaluate the noise effect in the temporal frames, a frame error is computed defined by,

$$e_{i,H}(k) = H_{i,t}(k) - H_{i,t+1}(k) \quad (2)$$

This error defines the difference in the two frame components, and low values and $\min(e_{i,H}(k))$ histogram errors are considered feature elements. However, this error observed during a frame observation period shows a large deviation and may be effective due to the noise effect. Therefore, in this coding, the intersection histogram will be a mode centered on the noise parameter. To remove this problem altogether and to improve feature selection more accurately, a histogram box computed over a time series is recommended. In this proposed approach, instead of retrieving the entire histogram from a single frame of information, a selection of histogram boxes is made. To select the box, the histogram boxes are initialized at random using the random weight factor.

$$H_i(k) = H_i(k)w(k) \quad (3)$$

Where,$w(k) = [w_0(k),\ w_1(k), \ldots\ldots, w_{M-1}(k)]^T$are the allocated weight factor for each frame.

The estimated error is then defined as;

$$e_{i,H}(k) = H_{i,t}(k) - H_i(k)w(k) \quad (4)$$

The error is recursively been computed over the total frames (i=1….N), and the initial error is recorded as $e_{i,H,init}$.

A weight factor is then updated as,

$$w(k+1) = w(k) + \mu \sum_{i=0}^{N-1} \frac{H_i^T(k)}{\|H_i(k)\|^2} e_{i,H,init}(k) \quad (5)$$

Where μ is the updation step size, with an error updation factor. The objective of this computation is to select the bins satisfying the $\min(e_{i,H}(k))$ condition.

The frame streaming error is minimized using the lowest mean error (LMSE) estimate. The Least Squares (LMS) algorithm is an adaptive algorithm that uses a steeply sloping gradient-based method. The LMS algorithm uses estimates of the available divergent gradient vector. The LMS contains a recursive procedure that performs the over-correction on the negative direction of the gradient vector, resulting in the lowest mean square error. Compared to other algorithms, the LMS algorithm is relatively simple; Correlation function calculation is not required and matrix inversion is not required. In the optimization of LMSE a gradient vector in the above weight update equation is computed as,

$$\Delta_w(E\{e^2(n)\}) = -2r+2Rw(n) \qquad (6)$$

The biggest problem in the steepest landing method is the related computation of real time detection of r and R matrices. This is calculated using the covariance matrices r and the instantaneous values of R instead of the original values.The LMS algorithm is initialized to an arbitrary value w (0) for the weight vector at n = 0. Correction of the weight vector results in a minimum value of the mean square error. For this reason, the LMS algorithm can be summarized in the following equations;

$$\text{Output},(n)=w^{h}\,x(n)$$

$$\text{Error, } e(n)=d^{*}(n)-y(n)$$

$$\text{Weight, } w(n+1)=w(n)+\mu x(n)e^{*}(n) \qquad (7)$$

This calculated weight provides an optimal value for noise reduction. Using this noise limit, the frames are denoised and transmitted for higher grid streaming. The experimental result obtained for the developed system is shown in the following section.

RESULTS AND DISCUSSIONS

To evaluate the method indicated for your performance analysis, a comparative analysis is performed on different video samples and frames. The results obtained are as illustrated in Figure 1.

(a) (b) (c) (d) (e)

Figure 1: Test samples considered for evaluation of streaming logic, (a) Football (b) Tennis (c) Terminator (d) Grandmother (e) Tajmahal

The result of the observation for the soccer sample is presented in Figure 2. The video sample is captured at a frame rate of 15 frames per second with a frame size of 200x150. The frames are read in a jump of 5 frames.

Figure 2: Extracted frames for processing (Ground truth)

Figure 3: Decimated frames at 1:2.5 to process

The sequence of the original frame is titrated to the scale factor 1: 2.5. The original frame sequence is considered as a ground truth sample for parametric evaluation, while the decimated sample is used for the streaming process. The sequence of decimated frames is illustrated in Figure 3. This frame sequence is processed through a different streaming logic and the proposed spectral coding and filtering logic to interpolate the frame back to the original frame size.

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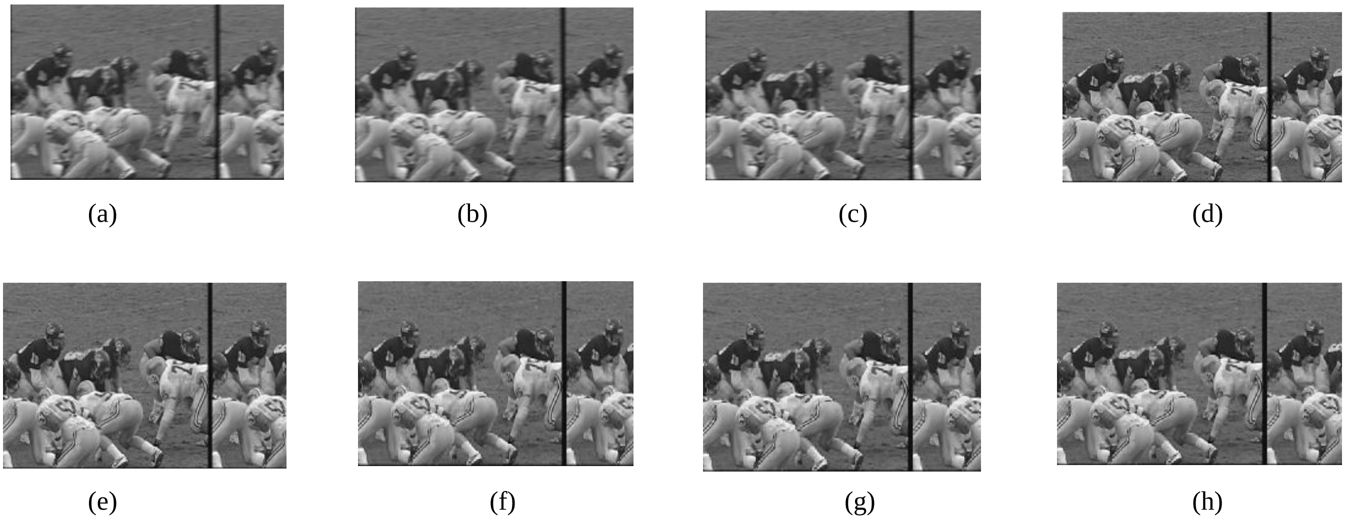

Figure 4: Interpolated results using (a) Closest neighbor (NNG), (b) Bi-Linear, (c) Bi-cubic, (d) Spline (e) FFT With 2D-wiener filter (g) Spectral streaming with 3D filtration

Figure 4 illustrates the frames obtained from the calculated streaming process over different coding approaches. In the closer neighbors streaming approach the blurriness effect is clearly seen. Where it is observed that the precision of the streaming is improved with other methods. In the case of bilinear and bi-cubic approach, the coding accuracy is observed higher. The best streaming is observed in the result of the spectral streaming (g) and the interpolated frames destroyed are observed in (h). These frame streaming operations are calculated for the parametric evaluation of accuracy and quality which are illustrated in the following figures.

Table 1: Observed PSNR for the test samples

Sample	Methods							
	NNG [1]	BL [1]	BC [1]	FFT [2]	Spline[1]	SC (proposed)	W-SC [3]	3D-SC (proposed)
S1	28.24	29.48	30.416	31.407	34.489	35.48	36.52	38.251
S2	28.46	29.02	30.39	31.46	31.96	32.40	33.82	36.85
S3	32.32	34.68	34.73	37.80	37.91	38.38	39.97	40.26
S4	32.45	33.36	34.23	35.21	35.54	36.20	37.72	39.02
S5	29.60	30.03	30.49	30.68	31.65	32.21	35.63	37.42

The observed PSNR parameter for the approach developed in different video frames have been evaluated and shown in Table 1. The PSNR is calculated by $PSNR = 10\log([\max(r(x, y))] / MSE)$, where x (i, j) is original image and y (i, j) is interpolated image. It is observed that the obtained PSNR improves from 28.24dB to 28.251dB. An average improvement of 10dB in PSNR is observed for the proposed 3D-correlative filters. The PSNR is improved by 8dB when applied with the spectral coding approach without applying the filtration operation. The computation time, MSE, PSNR, RRE, RMS and SSIM are compared with streaming approaches, these comparisons graphs are shown in Figure 5.

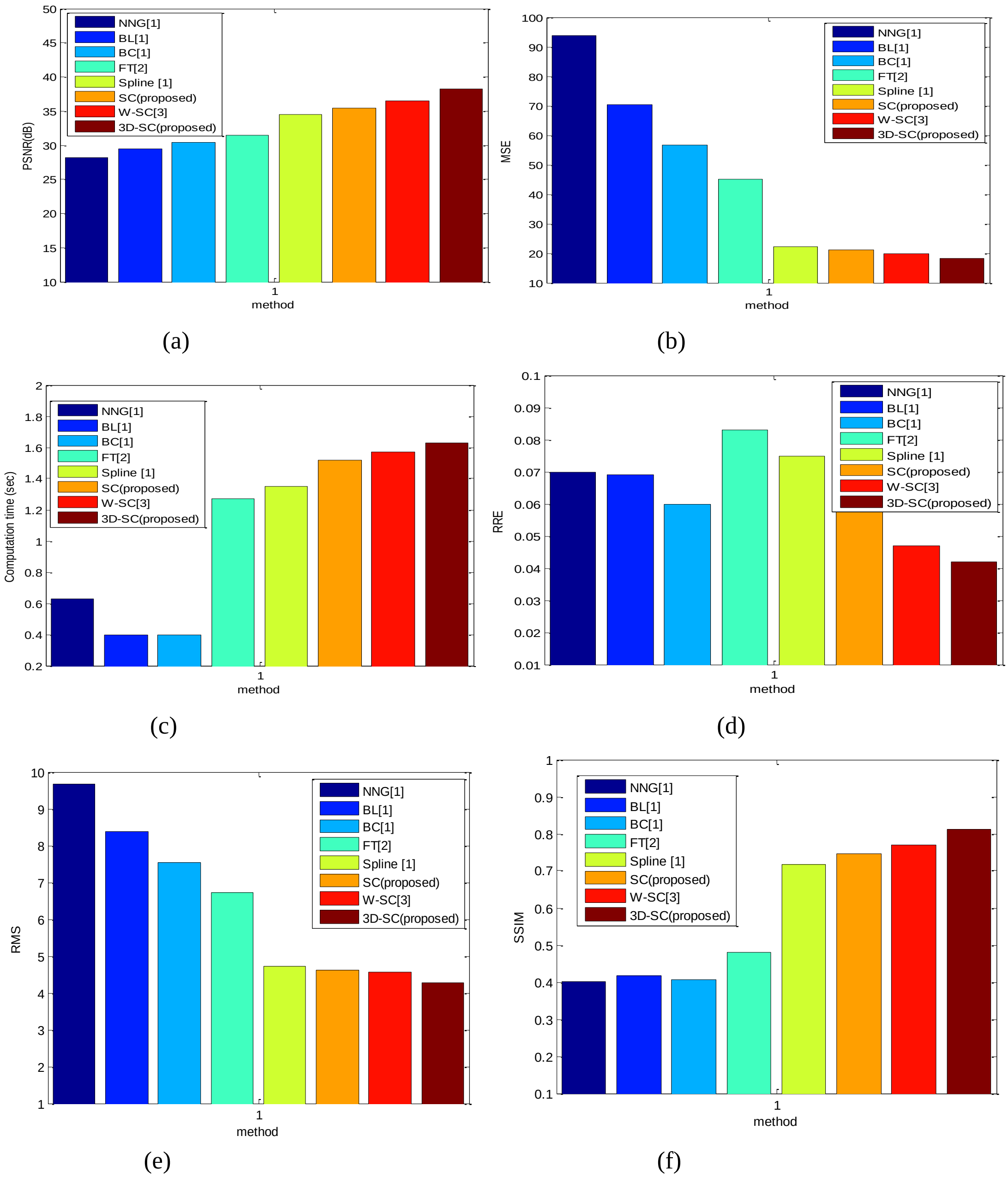

Figure 5: Comparison of the streaming approaches, (a) Computation time (sec), (b) MSE, (c) PSNR, (d) RRE, (e) RMS, (f) SSIM (football sample)

CONCLUSION

Towards the optimization of video streaming logic, a spectral domain coding is proposed using the spectral density selection process. The approach of streaming logic is defined by a spectral density selection process in which the spectral energy density for each resolution band is used for a band selection operation. In the specified spectral coding approach, the selected band coefficients result in a more pronounced streaming operation due to the larger selection. In the noise minimization approach in streaming, intra-frame correlation filtering logic is proposed. Intra-frame streaming results in optimum noise reduction and results in higher streaming accuracy. Observed metrics show improvement of streaming process compared to classical approaches.

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