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Analysis of Similarity Measure Techniques in Pixel Reconstruction based Video Error Concealment

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Abstract: In this paper, the effective spatiotemporal video error concealments (ECs) based on motion vector (MV) recovery and pixel-reconstruction methods are proposed. The pixel-based motion vector with partition (PMVP) algorithm predicts MVs of lost macro-blocks (MBs) based on the distance between the lost pixels and the available pixels of the surrounding MBs. For pixel reconstruction, Modified Spiral Pixel Reconstruction (MSPR) algorithm based on directional edge recovery method using minimum and maximum distance from available pixels of surrounding MBs is proposed. Most of the literature deals with Euclidean distance for recovering MVs or lost macro-blocks (MBs). In this work, PMVP and MSPR are modified by using various distance matrices like, Squared Euclidean distance, Manhattan distance, Minkowski distance, Chebyshev distance, Mahalanobis distance (MD), Canberra distances, Bray-Curties distance, Bhattacharyya distance, Hellinger distance and/or Kullback-Leibler divergence (KLD) distance etc., rather than Euclidean distance (ED) for recovering MVs. As MD uses standard deviation and covariance of available pixels, it give much better accuracy compared to Euclidean, Manhattan, Minkowski, Chebyshev, Cosine, Bray-Curties and Canaberra similarity measure techniques. Further, the MD gives more accuracy for non-square cluster compared to ED and its similar distance matrix approaches. It is proven that MD is most suitable and optimized distance calculation approach compared to various other types of distance calculus from Error concealment perspective. Mahalanobis similarity measures approach execute in less time compared to Bhattacharya, Hellinger and Kullback-Leibler divergence techniques. These proposed EC techniques are compared with existing EC techniques like, SPR and/or PMVP based EC with ED, and MV Interpolation by Zhou's method for various packet loss rates (PLRs) and quantization parameters (QPs). MPMVP with MD and KLD has higher *PSNR*s, as 24.62 dB and 24.74 dB respectively, as compared to PMVP with ED as 22.69 dB. Similarly, MSPR with MD and KLD has higher *PSNR*s, as 28.02 dB and 28.16 dB respectively, as compared to SPR with ED as 25.82 dB. Whereas the average execution time of MPMVP with MD is 0.3 sec compared to lowest the speed MPMVP with KLD technique as 0.8 sec. Similarly, the average execution time of MSPR with MD is 0.986 sec compared to lowest the speed MSPR with KLD technique as 2.168 sec. Due to such high *PSNR*s and comparatively less execution time, the proposed EC methods are implemented using Mahalanobis distance, which is more suitable for reconstructing errored video frame even for high packet loss rates over long distance transmission.

Keywords: Video processing, video compression, Error Concealment, Error Resilience, H.264/HEVC codec.

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I. INTRODUCTION

HD video gives a realistic and life like subjective viewing experience and this becomes a major area of research in television broadcasting, video streaming or video transmission technology. To improve existing video standards and its coding efficiency of multi-view video sequences, the Joint Video Team (JVT) introduced multi-view video coding (MVC) that is extended and prolonged by H.264/AVC [1]-[3].

EC, as a post processing method, recovers the lost blocks without modifying the encoder or channel coding schemes. The basic idea of EC is to estimate the corrupted blocks using correctly received blocks in the current video frame or adjacent frames. The reconstruction of video frames using EC can be classified into two approaches: Spatial Error Concealment (SEC) and Temporal Error Concealment (TEC). SEC extract lost/corrupted information within the current frames only, which will not provide exact substitution of lost macro-blocks.Whereas TEC recovers lost information from previous or next video frames,while fetching the information for future frames.The system need to hold the processes till the next frame reaches at the receiver end. This process further creates delay in the execution of the video transmission.

The Spatiotemporal Error Concealment (STEC) methods reconstruct lost MB from I-frame and/or P-frame and calculates the differences of boundaries. On the basis of such values, the decoder selects the most appropriate MB candidate for managing pixel reconstruction (PR). The spatiotemporal boundary matching algorithm (STBMA), efficient STBMA, and motion recovery using iterative dynamic-programing optimization

EC[4]-[5] approaches are limited to typical common resolutions of video frames like Common Intermediate Format (CIF) andQuarter CIF(QCIF), and the complexity of such ECs are quite high. A cluster is simply a collection of cases that are more similar to each other like a set of motion vectors of neighboring MBs belongs to the same video frame. The clustering of motion vectors divides a database into different groups. The goal of clustering is to find groups that are very different from each other, and whose members are very similar to each other. Clustering of motion vectors and spatial segmentation are similar but not the same methods. Segmentation refers to the general problem of identifying groups that have common characteristics in spatial domain. Clustering is a way to segment data into groups that are not previously defined, whereas classification is a way to segment data by assigning it to groups that are already defined. The analysis of various distance measurement techniques is required to find the similarity between the clusters of available motion vectors and the lost motion vectors. The most popular statistical distance calculi used in data clustering are Euclidean, Mahalanobis, Manhattan, Minkowski, Chebyshev, Cosine, Bray-Curties, Canberra, Bhattacharyya, Hellinger and Kullback-Leibler Divergence distance calculus.

II. PROPOSED SPATIOTEMPORAL ERROR CONCEALMENT IN VIDEO CODEC

Motion Vector Recovery is the primary step of most kind of Spatiotemporal EC algorithms. The motion vector recovery method uses pixel-based motion vector with partition (PMVP). There are various methods for MV recovery, such as PMVP, MV interpolation, MV estimation, etc. The MV recovery methods except PMVP predicts the lost MVs only from its cluster of surrounding available MVs. PMVP deals with the direction in which the surrounding MV comes from. Therefore, PMVP is preferred in this paper. PMVP algorithm is design by using Euclidian distance (ED) calculation for finding the similarities from the surrounded motion vectors available near lost MB. The proposed modified PMVP (MPMVP) replaces ED with Mahalanobis distance (MD) calculation. Because MD not only calculated the mean of distance between all surrounding available MVs like ED but also calculate the covariance matrix of the cluster of the set of available MVs for finding similarities between available MVs and the lost MV, which in turn increase the subjective quality of the reconstructed frame.

For experimental purpose let’s replace different types of distance calculus to find the most suitable for error concealment. The distances are normally used to measure the similarity or dissimilarity between two data objects. Some of the distance measures can be used to find lost MV from surrounded MVs in popular error concealment schemes are as follows:

Euclidean Distance:

The Euclidean distance between two data points involves computing the square root of the sum of the squares of the differences between corresponding values.

$$d_E(p_{i,j}, p_k) = \sqrt{\sum_{k=1}^{n}(x_{i,k} - y_{j,k})^2} \qquad (1)$$

x and *y* are the vectors of the location of the particular surrounding pixels and effective missing pixel. Euclidean distance only relate with position of the MVs and average values of the available motion vectors. This approach will not find the correlation of available cluster of MVs.

Mahalanobis Distance:

A generalized version of a Euclidean distance which has weights variables using the sample variance-covariance matrix. Because the covariance matrix is used this also means that correlations between variables are taken into account.

$$d_M(p_{i,j}, p_k) = \sqrt{(x-y)^T C^{-1}(x-y)} \qquad (2)$$

x and *y* are the vectors of the location of the particular surrounding pixels and effective missing pixel andC is the covariance matrix obtains from the location of all surrounding pixels.

Squared Euclidean Distance:

The Squared Euclidean distance metric uses the same equation as the Euclidean distance metric, but does not take the squared root.

$$d_{SE}(p_{i,j}, p_k) = \sum_{k=1}^{n}(x_{i,k} - y_{j,k})^2 \qquad (3)$$

Manhattan Distance:

It is also known as City block distance, and absolute value distance or L1 distance. Manhattan distances a distance that follows a route along the non-hypotenuse sides of a triangle. The name refers to the grid-like layout of most American cities which makes it impossible to go directly between two points. This metric is less affected by outliers than the Euclidean and squared Euclidean metrics.

$$d_{Man}(p_{i,j}, p_k) = \sum_{k=1}^{n}\left|(x_{i,k} - y_{j,k})\right| \qquad (4)$$

Minkowski Distances:

Minkowski distance is a generalization of both Euclidean distance and Manhattan distance.

$$d_{Mink}(p_{i,j}, p_k) = \sum_{k=1}^{n}\left|(x_{i,k} - y_{j,k})\right|^{\frac{1}{q}} \qquad (5)$$

where*q* is a positive integer.

Chebyshev Distance:

Chebyshev distance or (Tchebyshev distance), maximum metric, or L_∞ metric is a metric defined on a vector space where the distance between two vectors is the greatest of their differences along any coordinate dimension. The Chebyshev distance between two motion vectors is

$$d_{Cheb}\left(p_{i,j}, p_k\right) = \max(|(x_{i,k} - y_{j,k})|) \qquad (6)$$

Cosine Distance:

This is a type of Pearson measure which considers the relative difference, assuming that the scale is uniform (that the distance from zero is relative). In some case, this gives better results, particularly where the data is not normally distributed. It is a measure of similarity between two vectors of n dimensions by finding the cosine of the angle between them, often used to compare documents in text mining. In addition, it is used to measure cohesion within cluster in the field of data mining. Given two vectors of attributes A and B, the cosine similarity θ is obtained using a dot product and magnitude as shown in equation

$$Similarity = \cos(\theta) = \frac{A\ B}{(|A||B|)} \qquad (7)$$

Bray Curties distance:

Bray Curtis distance is also called Sorensen distance. It is a normalization method that is commonly used in botany, ecology and environmental science field. It views the space as grid similar to the city block distance. The Bray Curtis distance has a property that if all coordinates is positive, the value of the distance is between zero and one. Zero Bray Curtis distance represent exact similar coordinate. If both objects are in the zero coordinates, the Bray Curtis distance is undefined. The normalization is done using absolute difference divided by the summation as shown in equation

$$d_{Bray}\left(p_{i,j}, p_k\right) = \frac{\sum_{k=1}^{n}|(x_{i,k} - y_{j,k})|}{\sum_{k=1}^{n}|(x_{i,k} + y_{j,k})|} \qquad (8)$$

Canberra Distance:

Canberra distance examines the sum of series of a fraction difference between coordinates of a pair of objects. Each term of fraction difference has value between 0 and 1. If one of the coordinate is zero, the term becomes unity regardless of the other value. If both coordinates are zeros, the distance need to be defined as (0/0=0). This distance is very sensitive to a small change when both coordinates are near to zero. The Canberra distance is found using equation

$$d_{Canb}\left(p_{i,j}, p_k\right) = \sum_{k=1}^{n} \frac{|(x_{i,k} - y_{j,k})|}{|x_{i,k}||y_{j,k}|} \qquad (9)$$

Bhattacharyya distance:

The Bhattacharyya distance measures the similarity of two probability distributions such as two different clusters of motion vectors. It is closely related to the Bhattacharyya coefficient which is a measure of the amount of overlap between two statistical samples or populations in this case surrounding motion vectors of a lost MB. The distance is calculated as shown in (10).

$$d_{BhatC}\left(p_{i,j}, p_k\right) = -\ln\left(BC(p,q)\right) \qquad (10)$$

where, *p* and *q* are two discrete probabilities of domain X as a set of surrounded motion vectors and

$$BC(p,q) = \sum_{x \epsilon X} \sqrt{p(x)\ q(x)} \qquad (11)$$

The Bhattacharyya coefficient will be 0 if there is no overlap at all due to the multiplication by zero in every partition. This means the distance between fully separated samples will not be exposed by this coefficient alone. In video coding techniques, the clusters of motion vectors obtained are maintaining the similarity from its neighboring MBs and non-overlapping clustering of MVs are common phenomena. Hence Bhattacharyya coefficient will be 0 in most of the cases, which leads to be false prediction of lost motion vector.

Hellinger distance:

Hellinger distance is another distance measure used to quantify the similarity between two probability distributions. The Hellinger distance is defined as

$$d_H(P,Q) = \sqrt{\frac{1}{2}\sum_{i=1}^{k}\left(\sqrt{p_i} - \sqrt{q_i}\right)^2} \qquad (12)$$

where p_i and q_i are probability density functions of the two probability distributions, P and Q, being compared. Previously, Hellinger distance has been used in minimum distance estimation, which is a statistical method for fitting a mathematical model to data, usually the empirical distribution.

Kullback-Leibler divergence distance:

The Kullback-Leibler divergence - also known as the relative entropy, is a measure of how different two probability distributions (over the same event space) are. The KL divergence distance of probability distributions P, Q on a finite set χ is defined as

$$d_{KL}(P,Q) = \sum_{x \in X}\left((P(x) - Q(x))log\frac{P(x)}{Q(x)}\right) \qquad (13)$$

The KL divergence between P and Q can also be seen as the average number of bits that are wasted by encoding events from a distribution P with distribution Q. This KL divergence is a non-symmetric information theoretic measure of distance of P from Q. The smaller the relative entropy, the more similar is the distribution of the two variables, and conversely. This technique is more suited for finding dissimilarity between to clusters of motion vectors. The results obtained here is quite similar to Mahalanobis distance approaches, but the execution time required is more because of probability calculation.
The proposed Modified PMVP EC methods are arrived by following five major steps.

Step 1: H.264 Baseline codec implementation is very important procedure to design a compatible EC technique. The basic stages involve for implementing H.264 Baseline codec are as follows:
Encoder:
1) Setting input parameters: start /end Frame, Block size, QP
2) Read *.yuv file [qcif_444]
3) Motion Estimation Encoding process
Encode I frame as first frame
Intra frame prediction:
Transform, Quantization, Entropy coding,
Encode P Frames
*Motion Compensation:*Motion vectors/Motion data
Inter frame prediction:
Transform, Quantization, Entropy coding
4) Deblocking filters
5) Bit-stream data '*bitstreams.mat*'
H.264 encoder used to compress the video sequence by setting the initial parameters from the selected Group of Pictures (GOPs). The initial video frame is divided in *16* x*16*size MBs. Each block passed through integer DCT. DCT is further quantized after zig-zag scan. The higher is the QP, more DCT coefficient are neglected, hence more compression achieved.An uncompressed video is taken in **.yuv* file as QCIF videos (176 x 144 pixels) with chroma-sub-sampling 4:4:4. Motion estimation and compensation done on intra and inter frames of selected GOP. Transform coding quantization and Entropy coding convert video data into a single bit-stream. This bit-stream is transmitted to a noisy channel model.

Decoder:
1) Load transmitted original bit-stream
2) load *.yuv original video file [qcif_444] for Peak Signal to noise Ratio (*PSNR*) calculation
3) Decode header:
Height, width, QP, Frame_start, Frame_end, mode
4) Set Avg. Burst Length and Packet Loss Rate
Simulate channel Errors: Markov channel model
Packet loss (MB) Error
Generate ErrorMatrix
[Switch to Error Concealment Algorithms]
5) Decode P Frames
Using MV get MB from I-frame
*Motion Compensation:*Motion vectors/Motion data
*Motion predictions:*Intra / Inter
Transform, Quantization, Entropy coding
6) Deblocking filters
7) Return P frame and repeat step 5 for other p frame reconstruction
8) Find *PSNR* of all reconstructed frames, Avg. *PSNR* and Execution Time

H.264 decoder used to reconstruct the compressed bit-stream, obtained from encoder/transmitter model. Original video data is loaded to compare the reconstructed frames by calculating peak signal to noise ratio (*PSNR*). In decoder header, size of frames, QPs, types of GOPs are fetching initial information. Obtained bit-stream is passed through a noisy Markov channel model. Realistic errors are simulated by setting average burst length and packet loss rate. After this stage the proposed EC algorithms are executed. Most of the lost MV's are recovered by EC algorithms. Obtained MVs are passed throughmotion compensation and estimation blocked to reconstruct inter/intra frames. Inverse transform coding and entropy decoding are applied till all the P-frames are reconstructed. The deblocking filtering is used to correct the abrupt edges obtained while reconstructed MB's alignment.

Step 2: In this step the proposed MPMVP is explained. The motion vectors of lost Macro-block for each missing pixel location are derived and formulate by using available neighboring/ surrounded pixel motion vectors, which contribute to the generation and reconstruction of the missing motion vectors, which is inversely proportional to the distance between them [6]. The very first step is to formulate the generation of the errored and/or lost motion vectors to be a function of all adjoining and surrounding motion vectors. Further these MV's are weighted and generated by their distances. According to the encoding procedure to reconstruct streaming video data in the channel encoder, the pixels in a partition should go in the same direction. Therefore, finally, the motion vectors of pixels (estimated by the initial step) that belong to the same estimated partition (object) are forced to be the exactly same, in order to keep the integrity and reliability of moving objects or textural shapes. The algorithm of the modified pixel-based lost motion vectors are as follows:

1) Obtain and calculate motion vectors (horizontal and vertical both directions) for each pixel location present in the missing block of size 16 x16.
2) Every pixel-based MV to be recovered considers the adjoining or surrounded motion vectors in the closely existing neighboring pixel locations.
3) Each pixel-based MV to be recovered is considered to be inversely related in distance to its obtainablein adjoining or surrounding motion vectors. This is motivated by the fact that the motions (vectors) of two positions are less correlated when they are far apart.

Let us consider the said idea in the mathematical form; if the missing MB size is 16x16 then the 64 pixels are present in the surrounding. Location of each 64 such pixel can be define as p_k k=1:64, and the related motion vectors are MVx^{p_k}andMVy^{p_k} if$p_{i,j}$be the location of missing pixel in 16x16 MB, where i=1:16 and j=1:16, the corresponding MV of each missing pixel need to be found, say $MVx^{p_{i,j}}$and $MVy^{p_{i,j}}$. The distance between the points can be obtained as $d(p_{i,j}, p_k)$ and the contributing factor $\beta_k^{i,j}$ can be calculated as the reciprocal of the distance between the two points, as shown in (14) and (15).

$$\beta_k^{i,j} = \frac{1}{d_M(p_{i,j}, p_k)} \quad (14)$$

where,

$$d_M(p_{i,j}, p_k) = \sqrt{(x-y)^T C^{-1}(x-y)} \quad (15)$$

x and y are the vectors of the location of the particular surrounding pixels and effective missing pixel and$C$ is the covariance matrix obtains from the location of all surrounding pixels.

The lost motion vectors can be calculated as $MVy^{p_{i,j}}$ and $MVy^{p_{i,j}}$ as mention in (16) and (17),

$$MVx^{p_{i,j}} = \sigma_{i,j} \sum_{k=1}^{64} \beta_k^{i,j} \; MVx^{p_k} \quad (16)$$

$$MVy^{p_{i,j}} = \sigma_{i,j} \sum_{k=1}^{64} \beta_k^{i,j} \; MVy^{p_k} \quad (17)$$

where$\sigma_{i,j}$ is a distance normalization factor of pixel location $p_{i,j}$. The distance $d(p_{i,j}, p_k)$ can be considered as Euclidean distance or it will be replaced to Mahalanobis distance equation. Mahalanobis distance gives the information about how many standard deviations are away from point $p_{i,j}$ and the mean of the distribution of all known MV's surrounding pixels location. Such accuracy cannot be obtained from Euclidean distance calculation.

Step 3: The further alteration done on Modified PMVP algorithm explain in step 2, by replacing (15) with different types of distance measure calculation (3)-(13) one at a time. Hence obtain reconstructed video frames in each case. These reconstructed frames are used to compare various similarity measure techniques by finding *PSNR*s and execution time.

Step 4: EC algorithms can be done using a spiral-like pixel reconstruction (SPR) pattern on the H.264/AVC joint model simulation platform [9]. The proposed, modified spiral-like pixel-reconstruction (MSPR) algorithms deliver high accuracy and low complexity, and their subjective and objective evaluation results are superior to available EC algorithms. In initial step, the edge matching is applied to the boundary of lost macroblocks (MBs). In further steps, the directional edge group with the highest magnitude is selected and symmetric pixel referencing is performed along its orthogonal symmetry axis. The basic preprocessing of spiral pixel reconstruction approach is shown in Fig. 1. The conventional H.264/AVC scan mode used zigzag or scanline approach while SPR method can reference more adjacent relevant pixels. Hence, the reconstructed image has more continuous edges, resilient to a superior result. The sub-region partial-spiral STEC (P-STEC) techniques also add more accuracy in the system instead of total-spiral STEC (T-STEC).

In the P-STEC technique, the starting point of PR in the four sub-regions must first be resolute within the impaired MB. To complete a desired reconstruction result, every starting point must reference the most significant edge evidence around it. Selection of the edge which has the greater magnitudes inside the MB is done. Hence it is required calculate the distance between each pixel of that edge and the origin of the MB $P_{0,0}$ with the coordinates (i_0, j_0). Further identifying two such pixels, first one is the nearest and the second one is the farthest pixels from the origin, as the foundation for determining the starting point. Then recognize the nearest pixel location to either of the two pixels, either on their left or right, or on their top or bottom. If any pair of the pixel locations has a zero value, the nearest pixels on the left or right, or top or bottom of the edge pixel are considered the starting point. In such case no reconstruction has been performed at those pixels and thus no pixel values are generated. The distance between an edge pixel and the MB origin can be calculated either by Euclidean distance equation or by Mahalanobis distance.

$$d_{min}\ e_{i,j} = min\sqrt{(i-i_0)^2+(j-j_0)^2} \tag{18}$$

$$d_{max}\ e_{i*,j*} = max\sqrt{(i-i_0)^2+(j-j_0)^2} \tag{19}$$

From (18) and (19), Euclidean distance minimum and maximum values can be obtain, where $e_{i,j}$ and $e_{i*,j*}$ indicate the two closest pixels and farthest from the origin. In this case means and variance of the available pixel locations are not consider and hence the accuracy is not appropriate. Mahalanobis distance equations can serve this cause as shown in (20) and (21).

$$d_{M\_min}\ e_{i,j} = min\sqrt{(i-j)^T C^{-1}(i_0-j_0)} \tag{20}$$

$$d_{M\_max}\ e_{i*,j*} = max\sqrt{(i-j)^T C^{-1}(i_0-j_0)} \tag{21}$$

where*i* and *j* are the vectors of the location of the particular surrounding pixels and effective missing pixel at originand *C* is the covariance matrix obtains from the location of all surrounding pixels. It’s advisable to select Mahalanobis distance over Euclidean distance for getting better frame reconstruction.

Step 5: The further alteration done on Modified SPR algorithm explain in step 4, by replacing (15) with different types of distance measure calculation (3)-(13) one at a time. Hence obtain reconstructed video frames in each case. These reconstructed frames are used to compare various similarity measure techniques by finding *PSNR*s and execution time.

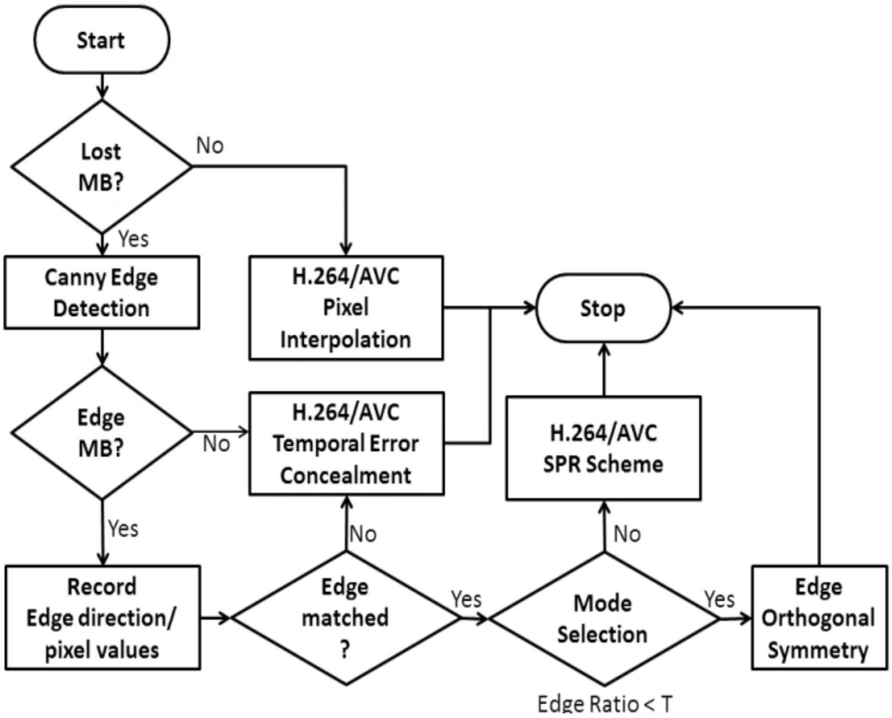
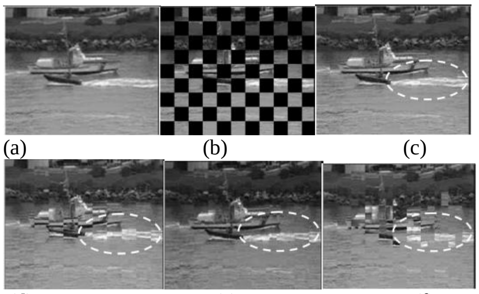


Figure 1:*Basic preprocessing steps for spiral pixel reconstruction.*

III. EXPERIMENTAL RESULTS

In this section the discussion is on the results obtain from reconstructed MPMVP and MSPR with various similarities measure equations. The proposed methods are compared with the other existing EC algorithms.

The video encoder selected as H.264 (Baseline code implement in Matlab® 2013, Intel® Core™ i7 processor with 4GB RAM) for the experimental settings. H.264 has some tools for error resilience including redundant slices and flexible MB ordering (FMO) [7]. The IPPPP as encoding GOP(group of pictures) structure with size 15 frames is used. The packetization scheme is "dispersed mode" in FMO. The packets are encoded/ lost in a checkerboard manner for better comparisons with other existing EC methods and proposed EC methods. Thus, there are two packets in a frame and 30 packets in a selected GOP. The quantization parameters (QPs) are fixed as 20, 24, 28, 32, and 36.The PLRs are consideredin a range of 3% (where error pattern of having random loss of one packet in a GOP) to 20% (where error pattern of having random loss of six packets in a GOP). The videos have a wide variety of motions and textures, and each video has 150 frames. Standard videos are taken as*coastguard*, *foreman* and *flower garden*. These standard parameters are kept common for comparison purpose with other available EC approaches. The concealed frames of all reconstructed methods are taken to compute the corresponding and matching *PSNR* against the original, uncompressed video. Error concealment performance for *coastguard* sequence (70th) in QP = 32 for packet loss rate 16% shown in Fig. 2. The reconstructed results are shown using PMVP, Zhou, MVE and Lie approaches and the comparison is done on the basis of *PSNR* parameter.This proves that the PMVP given much better EC results compared to other methods specified. Fig. 3 shows PMVP results when Euclidean distance used for calculated for missing MV, when Fig. 4 shows MPMVP results when Mahalanobis distance calculated for missing MV prediction. In case of square missing block Mahalanobis distance equation behave like Euclidean distance equation. Fig.5 shows Types of 16x8 block loss cases, Fig. 5(a) has checkerboard pattern error with packet loss rate 16% QP=64, while Fig. 5(b) indicate 16x8 block loss having all its surrounding blocks are present, having packet loss rate 8%.



(a) (b) (c)

(d) (e) (f)

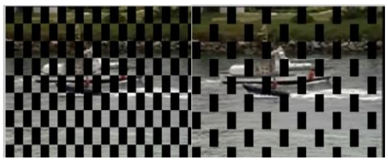
Figure 2:*Existing error concealment performance for coastguard sequence (70^{th} frame) in QP=32 for PLR 16% (a) original frame (b) error frame (c) PMVP [10], PSNR = 25.69 dB (d) Zhou [9], PSNR = 24.82 dB (e) MVE [1], PSNR = 25.17 dB (f) Lie [7], PSNR = 19.46 dB.*

(a) (b) (c)

Figure 3:*PMVP error concealment performance for coastguard sequence (70^{th} frame) in QP=32 for PLR 16% (a) previous frame (b) original current frame (c) reconstructed PMVP with Euclidian distance, MV averaging PSNR=22.695 dB.*

(a) (b) (c)

Figure 4:*MPMVP Error concealment performance for coastguard sequence (70th frame) in QP=32 for PLR 16% (a) previous frame (b) original current frame (c) reconstructed MPMVP with Mahalanobis distance, MV averaging PSNR=22.695 dB.*



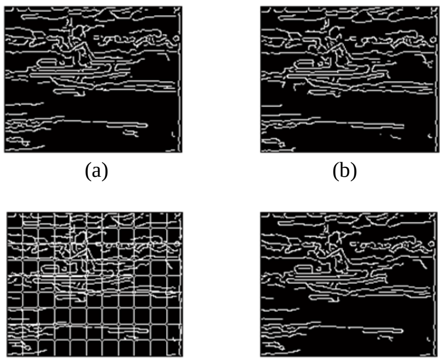
(a) (b)

Figure 5:*Types of 16x8 block loss cases, (a) checkerboard pattern error with packet loss rate 16% QP=64 (b) 16x8 block loss having all its surrounding blocks are present, having packet loss rate 8%.*

This case is used for verification for appropriate validation for comparing Mahalanobis and Euclidian distance EC approaches.The initial stage for spiral pixel reconstruction EC method is to find the canny edge detection of the video frames. Fig.6 and Fig.7 shows edge detected images of previous frame, original current fame, errored with Lost MB frame and reconstructed edge frames. To reconstruct the lost MB, every starting point should consider as a reference of most relevant edge information around it. For calculating distance between each pixel and the edge, that has the highest magnitude inside the MB from the origin of the MB and the corresponding coordinates of each pixel. The space and the gaps obtain between the connected lines for filling the reconstructed pixel information from spiral scanning, is not always symmetrical. The unsymmetrical gaps can get various standard deviations. Hence, Mahalanobis distance calculation is preferred compared to

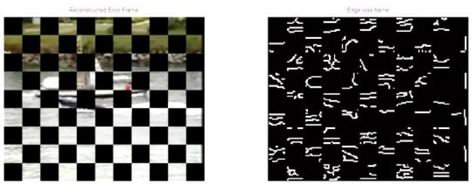
Euclidian distance calculations. The Mahalanobis distance gives the information about how many standard deviations are away from pixel pi,j and the mean of the distribution of all known MV's surrounding pixels location. Such accuracy cannot be obtained from Euclidian distance calculation. The reconstructed frame of SPREC is shown in Fig. 8.The blank space in few reconstructed MB indicate there are more than two lines are passing in the lost MB. To avoid this effect either way is to down partition the 16x16 blocks into 16x8, 8x16 or 8x8 as provided by H.264 video compression standards. Another way-out is to use pre-transmission algorithm to reduce the computational complexing for re-partitioning MB, as shown in Fig. 9. It is quite clear from Fig. 10 that Mahalanobis distance calculation used in proposed MSPR EC approache provides quite good quality reconstructed frames (*PSNR* obtained shown Fig.10, 24.62 dB is higher than all *PSNR*s values shown in Fig. 11-13) compared to Euclidean, Manhattan, Chebyshev, Cosine, Bray-Curties distance, and Canberra distance measure calculations done in proposed system. The main reason for *PSNR* boost is that, the error patterns are rectangular shape instead of square shape as shown in Fig.4, Mahalanobis distance are more accurate when distributed samples are elliptically spread rather than circular. When the covariance matrix is identity matrix, the Mahalanobis distance is the same as the Euclidean distance, due to this if MB are with fixed square size like 16x16, 8x8 etc., and surrounding MBs moving in the same direction (as fetch MVs states), the output results gives similar *PSNR*, but when MB are variable size like 16x8, 8x16, 8x4, 4x8 etc. (block partitioning in H.264 codec), and surrounding MB having different MV's than the Mahalanobis gives better results compared to Euclidean distance method. The Bhattacharyya, Hellinger and Kullback-Leibler Divergence Similarity measurement approaches are giving much better *PNSR* while error frame reconstruction with a cost is slow processing speed compared to Mahalanobis distance approach.

The various existing EC methods on standard video sequences are implemented and the *PSNR* values are calculated from the each reconstructed frames. The average *PSNR* of *coastguard* (*cg*), *foreman* (*f*) and *flower garden* (*fg*) standard video sequences are tabulated for comparison in the Table 1, Table 2 and Table 3.



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

Figure 6: *Canny edge detection of adjacent frames with MB partition and edge spiral reconstruction for coastguard sequence (70th frame) in QP=32 for PLR 16% (a) canny detection on previous frame (b) canny detection on current frame (c) MB wise division of canny output (d) reconstruct edges of lost MB by spiral scanning.*



(a) (b)

Figure 7: *Checker board error in coastguard sequence (70th frame) in QP=32 for PLR 16% (a) lost MB current frame (b) canny edge extracted frame.*

Figure 8: *Reconstructed frames by only SPR Error Concealment Algorithm.*

(a) (b) (c)

Figure 9:*(a) previous frame (b) original current frame (c) reconstructed MSPR EC with Mahalanobis technique, PSNR=26.42dB.*

(a) (b) (c)

Figure 10:*(a) original frame (b) reconstructed MSPR with Mahalanobis Distance, MV Averaging PSNR=28.022 dB (c) reconstructed MPMVP with Mahalanobis Distance, MV Averaging PSNR=24.62 dB, type of 16x8 block lost condition shown in Fig 5(b).*

(a) (b) (c)

Figure 11:*Reconstructed frame (a) MSPR with Euclidean Distance, PSNR=25.82 dB (b) MSPR Manhattan distance, PSNR=21.43 dB (c)MSPR with Chebyshev distance PSNR=17.82 dB, type of 16x8 block lost condition shown in Fig 5(b).*

(a) (b) (c)

Figure 12:*Reconstructed frame (a) MSPR with Cosine Distance, PSNR=22.72 dB (b) MSPR Bray Curties Distance, PSNR=26.34 dB (c) MSPR Canberra Distance, PSNR=26.60 dB*

(a) (b) (c)

Figure 13:*Reconstructed frame (a) MSPR Bhattacharyya distance, PSNR=26.06 dB (b) MPMVP Bray Hellinger Distance, PSNR=26.9dB (c) MSPR Kullback-Leibler Distance, PSNR=28.16 dB*

Table 1
Various Existing EC methods with their*PSNR*

Methods	***PSNR* in dB**		
	coast guard	***foreman***	***flower garden***
H.264 no error no EC [1]	28.69	24.3148	19.4417
H.264 with Error No EC [1]	23.07	22.8493	18.6667
MVE by Zhou [8]	26.27	23.8023	18.7615

Table 2
Analysis of various similarity measure techniques in proposed MPMVP EC method

Methods	**Quality and Execution time of reconstructed video Frames**					
	coast guard		***foreman***		***flower garden***	
	PSNR(dB)	**Time** (Sec)	***PSNR*** (dB)	**Time** (Sec)	***PSNR*** (dB)	**Time** (Sec)
PMVP with Euclidean Distance [6]	22.695	0.137	23.491	0.135	18.149	0.165
PMVP with Squared Euclidean Distance	20.426	0.130	21.142	0.128	16.334	0.157
MPMVP with Mahalanobis Distance	24.624	0.365	25.487	0.358	19.691	0.396
MPMVP with Manhattan Distance	18.837	0.112	19.498	0.111	15.064	0.135
MPMVP with Minkowski Distance	17.475	0.164	18.088	0.162	13.975	0.198
MPMVP with Chebyshev Distance	15.660	0.110	16.209	0.108	12.523	0.132
MPMVP with Cosine Distance	19.972	0.260	20.672	0.257	15.971	0.314
MPMVP with Bray-Curties Distance	23.149	0.315	23.961	0.311	18.512	0.380
MPMVP with Canberra Distance	23.376	0.343	24.196	0.338	18.693	0.413
MPMVP with Bhattacharyya Distance	22.900	0.475	23.703	0.465	18.313	0.515
MPMVP with Hellinger Distance	23.639	0.675	24.468	0.662	18.903	0.733
MPMVP with KL Divergence Distance	24.747	0.803	25.614	0.788	19.789	0.871

Table 3
Analysis of various similarity measure techneques in proposed MSPR EC method

Methods	Quality and Execution time of reconstructed video Frames					
	coast guard		*foreman*		*flower garden*	
	PSNR (dB)	**Time** (Sec)	***PSNR*** (dB)	**Time** (Sec)	***PSNR*** (dB)	**Time** (Sec)
SPR EC with Euclidean Distance [9]	25.827	0.617	26.733	0.608	20.654	0.743
SPR EC with Squared Euclidean Distance	23.245	0.585	24.060	0.576	18.588	0.707
MSPR EC with Mahalanobis Distance	28.022	0.986	29.004	0.967	22.408	1.069
MSPR EC with Manhattan Distance	21.437	0.504	22.189	0.500	17.143	0.608
MSPR EC with Minkowski Distance	19.887	0.738	20.584	0.729	15.904	0.891
MSPR EC with Chebyshev Distance	17.821	0.495	18.446	0.486	14.251	0.594
MSPR EC with Cosine Distance	22.728	1.170	23.525	1.157	18.175	1.413
MSPR EC with Bray-Curties Distance	26.344	0.851	27.268	0.840	21.067	1.026
MSPR EC with Canberra Distance	26.602	0.926	27.535	0.913	21.273	1.115
MSPR EC with Bhattacharyya Distance	26.060	1.283	26.974	1.256	20.840	1.391
MSPR EC with Hellinger Distance	26.901	1.823	27.845	1.787	21.512	1.979
MSPR EC with KL Divergence Distance	28.162	2.168	29.149	2.128	22.520	2.352

The average results tabulated of reconstructed frames in QP = 32, for packet loss rate 16% implemented with H.264 baseline codec having no error and no EC, with error and no EC, and MVE [6]. MVE approach is based on average MV calculation. When there is no error the reconstruction by H.264 decoder set the highest margin of the *PSNR* in each video sequence. The idea is to achieve this range of *PSNR* from the proposed EC techniques. The closest *PSNR* will decide the best EC approach. The average *PSNR* in dBs and execution time in seconds are tabulated for reconstructed video frames having common QP as 32 and similar packet loss rate as 16%. The implementation done with H.264 baseline codec for EC approaches using various distance calculations for predicting lost MVs. Table 2 and Table 3 indicate the average *PSNR*s and execution time of reconstructed MPMVP and MSPR with numerous similarity measure techniques. The average *PSNR*s of top four techniques such as KL Divergence, Mahalanobis, Hellinger and Canberra distance measure are 23.38, 23.27, 22.34, and 22.09 dB respectively for MPMVP EC, same way the average *PSNR*s of top four techniques such as KL Divergence, Mahalanobis, Hellinger and Canberra distance measure are 26.61, 25.2, 25.42, and 25.14 dB respectively for MSPR EC. The slowest techniques in MPMVP (MSPR) as KL Divergence and Hellinger distance measure with average execution time as 0.82 (2.2) and 0.69 (1.86) seconds respectively.

IV. CONCLUSION

In this paper, an effective spatiotemporal error concealment algorithm based on modified PMVP (MPMVP) and Modified SPR (MSPR) ECs are proposed. The encoding partition in lost MB is estimated and predicted by MPMVP and MSPR with various similarity measure approaches. The valuations in the network environment of packet loss rate (PLR) 3%, 7 %, 16%, and 20% and by setting quantization parameters (QP) such as 20, 24, 28, 32, and 36 for video sequence *coastguard* (*cg*), *foreman* (*f*) and *flower garden* (*fg*) are considered.

MPMVP with similarity measure techniques which can correlate the clusters of available neighboring MVs has reconstruct errored frame with higher *PSNR*s such as KL Divergence, Mahalanobis, Hellinger and Canberra distance measure. The Bhattacharyya distance measure approach also gives satisfactory result, particularly when there are only two types of MVs clusters available, but this combination is not so frequent in video coding. The fastest techniques are, Chebyshev, Manhattan and Squared Euclidean distance having average execution time for MPMVP (MSPR) EC as 0.117 (0.525), 0.119 (0.537) and 0.138 (0.623) seconds respectively with the low value of *PSNR*s as 14.8 (16.84), 17.8 (20.256), and 19.3 (21.96) dB respectively. The KL Divergence distance also consider for compressed video data storage and display. Since the average execution time is quite high as 0.82 (2.216) sec, KLD measure is not suited for live video streaming. As the optimized solution the Mahalanobis distance measure had average *PSNR* 23.27 (26.478) dB and execution time 0.37 (1.007) seconds, consider to be the best approach among all the similarity measure techniques mentioned in the proposed paper.

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