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A Novel Video Compression Artifact Reduction Scheme Based on Optical Flow Consistency

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ABSTRACT

In today's electronic world, day-to-day activities are captured as a video and store it into a drive as their memory. The media processing 26 industries are growing suddenly and attain the peak level due to this drastic improvement of video needs. In this sense, video compression is the major part to deal with, because the size of video is usually large. The requirement to store the video into the drive requires huge space and memory. So, that a new technique is introduced in this paper, to compress the video. Video compression algorithms are widely used to reduce the huge size of video data, but they also introduce unpleasant visual artifacts due to the lossy compression. To obtain a high quality images/videos at the decoder side, a lot of compression artifact reduction algorithms have been proposed to generate artifact-free images in the past decades. Previously, manually designed filters and sparse coding based methods are proposed to solve this problem. In this project, Lucas Kanade based Optical flow detection for compression artifact reduction is proposed. The strategy first partitions every video outline into suspicious and evidently honest parts. So an optical stream coefficient is registered from each part. Phonies are found when an unordinary incline in the optical stream coefficient of the suspicious article is identified. An extensive experimental result on the Vimeo-90k and HEVC benchmark datasets demonstrate the effectiveness of the proposed method.

Index Terms—Lucas Kanade based Optical flow, video compression, Compression artifact reduction, Optical flow model, recursive filtering, video restoration.

I. INTRODUCTION

Compression algorithms have been applied to reduce the storage size and bandwidth for the increasing amount of video data. Video compressor can provide more accurate and consistent temporal information, which produces higher quality restoration and compression results. In addition, the strong video compressor uses as prior information of prediction residual is also exploited for restoration through a well-designed neural network. Considering the increasing amount of video data over the Internet, compression algorithms (e.g., H.264 and HEVC) have been applied to reduce the storage size and bandwidth.

In order to obtain high quality images/videos at the decoder side, a lot of compression artifact reduction algorithms have been proposed to generate artifact-free images in the past decades. Compression artifact reduction techniques target producing artifact-free pictures from lossy decoded pictures. To store and move a lot of pictures and videos on the Internet, picture and video compression methods (e.g., JPEG, H.264) are generally utilized [1][3]. Strategies have been created in the previous few decades. Early works utilize physically planned filters [4][5] and sparse-coding techniques [6][7][8][9] to eliminate Compression artifacts. As of late, convolution neural network (CNN) based methodologies have been effectively applied for a great deal of PC vision errands [10][11][12][13][14], for example, super clarity/resolution [15,16], denoising [17] and artifact decrease [18][19][20]. Specifically, Dong'et al. [18] firstly proposed a four-layer neural organization to take out the JPEG Compression artifact rarities.

For the video artifact decrease task, our inspirations are two-fold and to start with, the rebuilding cycle for the current casing could benefit from the past reestablished outlines. An explanation is that when contrasted with the decoded outline, the past reestablished casing can give more exact data. Thusly fleeting data, (for example, movement pieces of information) from neighboring edges is more exact and hearty, and can give the possibility to additionally improve the exhibition. Moreover, the reliance of past reestablished outlines normally prompts a recursive pipeline for video artifact rarity decrease. Along these lines it recursively reestablishes the current casing by possibly using all past reestablished outlines, which implies we can use effective data engendered from past assessments. Presently, the majority of the state-of-the-art deep learning approaches for Compression antique decrease are restricted to eliminate artifacts in a solitary picture [16][17][18][19]. In spite of the fact that the video artifact decrease strategy [21] or video super resolution strategies [22][20] attempt to integrate temporal data for the reclamation undertakings, their techniques overlook the past reestablished outline and reestablish each casing independently as appeared in Fig.1(a). Along these lines, the video artifact decrease execution can be additionally improved by utilizing a fitting dynamic filtering plan. Second, present day video Compression methods may contain incredible earlier data that can be used to reestablish the decoded outline. It has been seen that reasonable video Compression principles are not ideal as indicated by the data hypothesis [9];

II. RELATED STUDY

A lot of methods have been proposed to remove the compression artifacts. Early methods [25] designed new filters to reduce blocking and ringing artifacts. One of the disadvantages for these methods is that such manually designed filters cannot sufficiently handle the compression degradation and may over smooth the decoded images. Learning methods based on sparse coding were also proposed for image artifact reduction [8][9]. Chang et al. [8] proposed to learn a sparse representation from a training image set, which is used to reduce artifacts introduced by compression. Liu et al. [9] exploited the DCT information and built a sparsity-based dual domain approach. Recently, deep convolutional neural network based methods have been successfully utilized for the low-level computer vision tasks. Dong et al. [18] proposed artifact reduction CNN (ARCNN) to remove the artifacts from JPEG compression. Inspired by ARCNN, several methods have been proposed to reduce compression artifact by using various techniques, such as residual learning [21], skip connection [22], batch normalization [17], perceptual loss [30], residual block [20] and generative adversarial network [20]. Due to the popularity of neural networks for image restoration, several CNN based methods [21][22] were also proposed for the video restoration tasks. For video super-resolution, Liao et al. [14] first generated an ensemble of SR draft via motion compensation, and then used a CNN model to restore the high resolution frame from all drafts. Kappeler et al. estimated optical low and selected the corresponding patches across frames to train a CNN model for video super-resolution. Based on the spatial transformation network (STN) [16], the works in [21][20] aligned the neighboring frames according to the estimated optical low or transform parameters and increased the temporal coherence for the video SR task. Tao et al. [22] achieved sub-pixel motion compensation and resolution enhancement with high performance. Xue et al. [21] utilized a joint training strategy to optimize the motion estimation and video restoration tasks and achieved the state-of-the-art results for video artifact reduction. Compared to the methods for single image compression artifact reduction, the video restoration methods exploit temporal information. However, these methods process noisy/low-resolution videos separately without considering the previous restored frames. Therefore, they cannot improve video restoration performance by utilizing more accurate temporal information. In our work, we recursively restore each frame in the videos by leveraging the previous restored frame for video artifact reduction.

III. SYSTEM METHODOLOGIES

A. Proposed Approach

In this project Lucas Kanade based optical flow is proposed for video compression artifact reduction. First, the restoration process for the current frame can benefit from the previous restored frames. It is expected that the previous restored frame can provide more accurate temporal information compared with the original decoded frame. Therefore more precise temporal information from previous restored frames and build a robust video artifact removal system with high performance can be employed. It is obvious that the dependence of previous restored frames will lead to a dynamic recursive solution for video artifact removal. Although the temporal information is utilized in video artifact reduction or video super resolution, each frame is restored separately without considering the previous restored frames. In summary dynamic filtering scheme to exploit accurate temporal information in previous frame for high quality restoration will be build.

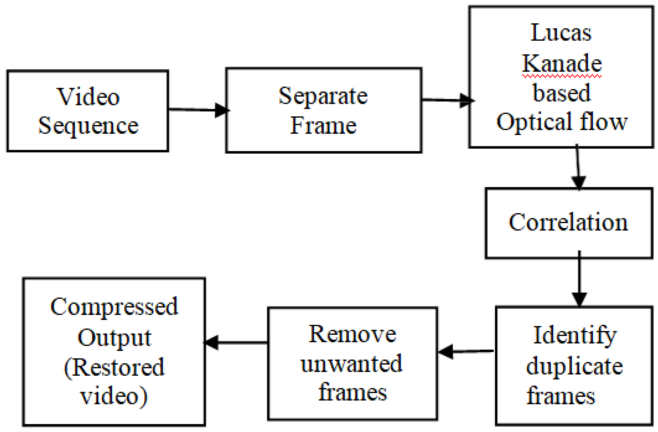


Fig.1 Proposed System - Block Diagram

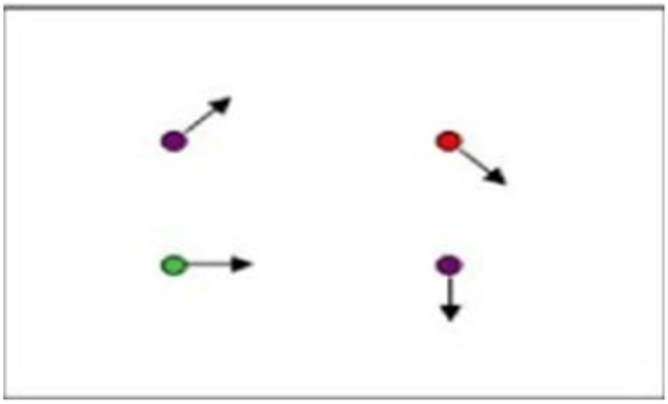
B. Video Sequence

Video sequence is an arrangement of video, audio and graphics (text) clips on the timeline which is ready to restore frames. A non-local frame changing sequence differs video correlation at the time of identifying duplicate image. Video sequence sets the complete process and separates the frame towards the optical flow, which arranges towards deep frames changing model.

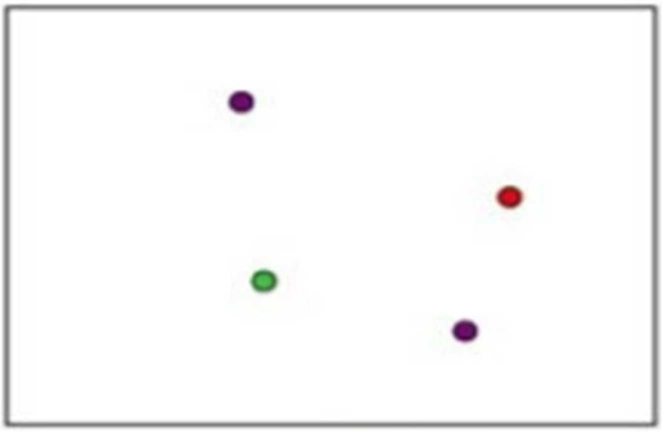
C. Optical Flow

Optical flow is the distribution of apparent movement velocities of brightness patterns in videos, which can give important information about the image spatial arrangement and change rate of objects. However, differential method is widely used technique in optical flow, also there are many methods of estimating the optical flow between two frames, including differential-based, region-based, energy-based, and phase-based methods. Differential method is the technique in optical flow which is based on the assumption of image brightness constancy. The optical flow equation can be assumed to hold for all pixels within a window centered at p. Optical flow has more equations than unknowns and thus it is usually over-determined.

Consider an Image intensity (I) as a function of space (x,y) and time (t) and move its pixel by (u,v) over t time and obtained a new image.



I(x,y,t-1)



I(x,y,t)

Fig.2 Estimating Optical flow

D. Correlation

The basic image operations of correlation, convolution and some aspects of one of the applications of convolution, image filtering. Image correlation and convolution differ from each other by two mere minus signs, but are used for different purposes. The following equation, Eqn(1) shows the Correlation formula.

$$\rho_{xy} = \frac{Cov(r_x, r_y)}{\sigma_x \sigma_y} \quad \ldots (1)$$

Value of correlation is limited between -1 and +1 and can be interpreted as follows: -1: If it is -1 then variables are known as perfectly negatively correlated. That means if one variable is moving in one direction then another is moving in the opposite direction.

E. Duplicate Frame Identification

Optical flow and their high and stable correlation in copy-move tampered videos offer basics for effective detection. For calculation cost reasons, the consistency of Optical flow is analyzed first to locate suspected tampered positions. The process will help to reduce multiple calculations and comparisons of correlation matrices, but may lead to more false detections. Fine detection based on Optical flow correlation is then proposed to match the duplicated frame pairs, and reduction of false detections based on validation checks will be conducted further for precision.

F. Unwanted Frame Removal

It is worth nothing that fine detection for copy-move forgeries depends on the coarse detection results with abnormal points in OF sum sequences. In fine detection based on correlation analysis, adjacent frames with high similarity will also lead to false alarms. Besides, additional operations may be performed after copy – move forgery to cause interference and cover up the abnormities.

IV. RESULTS AND DISCUSSIONS

The proposed system of video compression based on Optical flow and its processes are experimentally done by using MATLAB, which is a general and well-known software used for most of the Digital Image Processing and Media Processing applications. As well the accuracy parameters are measured clearly and the proofs of all accuracy measurements are summarized and visualize below. From the input video, the video is divided into number of frames, getting the divided frames from the key frame folder.

The following figure, Fig.3 shows the optical flow is analyzed by comparing the correlation of each pixel in the frame with one another. The divided frames shows the comparison between each frame, which is corrected towards output.

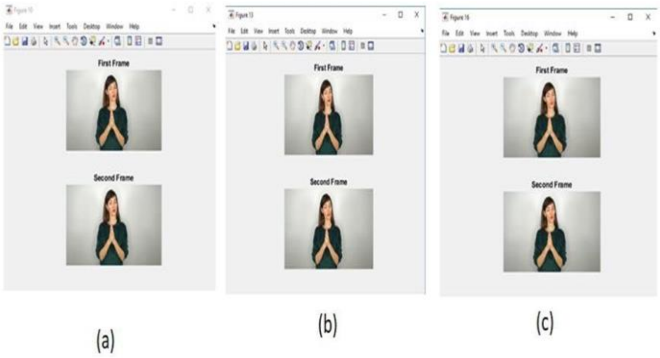
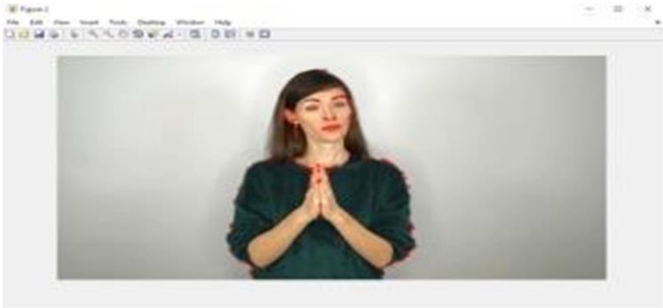


Fig.3 Correlation Comparison between Frames;
(a) Comparison between frame 1 & 2, (b) Comparison between frame 3 & 4 and (c) Comparison between frame 5 & 6.

The following figure, Fig.4 shows the optical flow of each frame is now calculated after comparison. Optical flow of vectors are modified and compared in each frame.

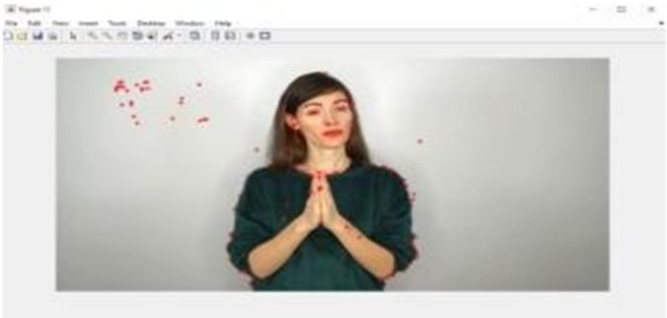
Fig.4Vector Optical Flow Comparison between Frames;
(a) Optical flow vector of Frame 1 & 2, (b) Optical flow vector of Frame 3 & 4 and (c) Optical flow vector of Frame 5 & 6.

The following figure, Fig.5 shows the corners of the objects in the frames are found and then the values are partially differentiated in x and y direction with respect to time.



(a)

(b)



(c)

(d)

Fig.5 Frame Corner Comparison; (a) Corners of Frame 1 & 2, (b) Corners of Frame 3 & 4, (c) Corners of Frame 5 & 6 and (d) Corners of Frame 7 & 8.

V. CONCLUSION

Video compression is gaining popularity since storage and network bandwidth requirements are able to be reduced with compression. Many algorithms for video compression which are designed with a different target in mind have been proposed. This study explained the standardization efforts for video compression such as H.261, 263 and 263+, MPEG-1, 2, 4, 7 and H.264. Most recent efforts on video compression for video have focused on scalable video coding. The primary objectives of on-going research on scalable video coding are to achieve high compression efficiency high flexibility (bandwidth scalability) and/or low complexity. Due to the conflicting nature of efficiency, flexibility and complexity, each scalable video coding scheme seeks tradeoffs on the three factors. Designers of video services need to choose an appropriate scalable video coding scheme, which meets the target efficiency and flexibility at an affordable cost and complexity.

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