A NOVEL VIDEO COMPRESSION THEN RESTORATION ARTIFACT REDUCTION METHOD BASED ON OPTICAL FLOW CONSISTENCY TO IMPROVE THE QUALITY OF THE VIDEO

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ABSTRACT

In the recent days, the multimedia communication is created enormous impact in transmission and reception of data. In the multimedia communication, the video transmission, reception and storage are playing significant role. The requirement to store the video into the drive requires huge space and memory. The video compression methodology is segmented into two classes; first is lossy compression and next is lossless compression. In the lossy compression, the video frames are compressed high comparatively than lossless compression but after than compression, the video quality becomes poor due to the occurrence of artifacts. In this research, an innovative methodology is implemented to compress the video frame by applying the artifact reduction technique. The video frame data compression techniques could be significantly applied for reducing the huge size of video frame content, but they also produce objectionable visual artifacts due to making the lossy compression. The proposed methodology is used to enhance the quality of the video after compression by applying Deep Recursive Ensemble Particle Filter (DREPF) technique to remove artifacts. Particularly, the video quality improvement after compression is designed as a Recursive Ensemble Particle Filtering (REPF) process and the decoded video frames could be enhanced from the proposed DREPF. In the proposed methodology, Deep Convolutional Neural Network (DCNN) is implemented to calculate the equivalent positions in the Recursive Ensemble Particle Filter (REPF) and incorporated mutually in the deep Recursive Ensemble Particle Filtering. More significantly, the preceding information is estimated by integrating the time and temporal system for better enhancement of video frames. The proposed methodology obtains the benefits of the model-based system and learning-based system, by incorporating the recursive nature of the Recursive Ensemble Particle model and dominant illustration capability of DCNN. The results of experiments show that the proposed methodology gives better results than existing systems.

Keywords: Deep Convolutional Neural Network (DCNN), Deep Recursive Ensemble Particle Filter (DREPF), Lossless compression

Introduction

Video frame Compression techniques have been applied to reduce the disc flexibility and scalability for the greater frequency of video frames. Video frame compression may provide more precise and accurate temporal features, helping to enhance the accuracy and compression reliability of efficiency restoration [1]. In specific, a well-designed computer program often uses the powerful video frame compression is used as the preceding dependent pixel values for restoration. In view of the rising amount of video frame information over data storage, compression methods have been designed to minimize processing power and device capacity. In order to attain maximum images on the decoder side, a lot of compression artifact reduction systems have been recommended in past years to generate artifact-free artifacts [2]. Video frame compression artifacts control strategies seek to produce artifact-free objects from lossy decoded videos. Photos and video encoding techniques are widely used on the Internet to store and retrieve a large number of pictures and videos. Nevertheless, these methods also show undesirable compression artifacts, such as blocking, perverting, and roaring old artifacts. Therefore, the decrease in the scarcity of compression artifacts has been taken into account and different methods have been applied in the last few decades [3]. Early work uses progressively built detectors and sparse-coding strategies to eliminate compression artifacts. As of late, for a wide variety of PC vision errands, such as super objectivity, de-noising and artifact reduction, techniques based on the convolution neural network (CNN) have been effectively used [4]. In particular, Dong et al. firstly recommended the removal by a four-layer neural network system of the JPEG Compression artifact rarities. For the video artifact reduction competition, our designs are two-fold and will profit from the restored specifics of the past to continue with the reconstruction cycle for the current event [5]. One explanation is that, as opposed to the decrypted model, the previously re-established case would have more detailed information. Flashing data from adjacent boundaries (for example, data operation fragments) is therefore more reliable and heartfelt, and can issue the possibility of further improving the show [6]. Moreover, dependence on re-established past outlines usually allows the artifacts of video objects to be minimized by a recursive mechanism. In accordance with these words, it iteratively re-establishes the following cases by possibly using all previous re-established information, which means that effective data generated from service delivery can be used. Most of the province machine learning techniques for minimizing antique saturation is currently restricted to the single image removal of objects [7]. While the analysis method for video artifacts or based image video strategies are trying to integrate sequential specifics for remediation efforts, their methods disregard the previously re-established structure and restore each case separately. Along these lines, the video artifact removal output will be further improved by using an appropriate adaptive filtering process. Second, today's video's encoding methods will contain incredible previous knowledge which can be used to retrieve the decoded outline [8]. As indicated by the principle of data, it has been shown that logical specifications for video frame compression are not ideal; therefore, the resultant compression code sources can have redundant information. In any event, realistically, by leveraging the details covered in the code networks, it is possible to maximize the impact of reconstruction. For video frame compression techniques, inter-estimation is a simple technique used to minimize statistical formulas. The decoded frame then consists of a two-frame projection and a quantized projection leaving. The region with high distortion also corresponds to the residual values of the high sub-band prediction. The difference between both the initial frame and the decoded image are specified. It is therefore necessary to reinforce the restoration by using previous experience of this challenge [9]. Object reduction results among (c) Xue et al. [10] and (d) the proposed deep local threshold network are executed. (e) Original image (f) Decoded image (g) Quantization of the persistent expectation (h) Discrepancy between the initial data and the data decoded. In this paper, for video artifact elimination, a deep Recursive Ensemble Particle filtering network is proposed. As a post-preparation process, the proposed solution can be used and can also be extended to various types of compression. Specifically, the reduction problem model of the video artifact are represented as a form of Recursive Ensemble Particle filtering, which can recover the decoded casing recursively and collect details that proliferated from previous restored outlines. Two DCNN is used to conduct Recursive Ensemble Particle filtering for decoded outlines: the calculation network and the projection network. The forecasting network plans to have an earlier appraisal based on the re-established outline of the past [11]. At the same time, the quantize expectation remaining in the coding methods is explored and a novel net approximation centralizing this strong earlier evidence is introduced for powerful calculation. The restored edge can be obtained from that point onward by integrating the previous evaluation and the estimate under the Recursive Ensemble Particle framework. By combining the recursive concept of the Recursive Ensemble Particle model and the fundamentally non-straight transition capability of neural network, our proposed approach overcomes every obstacle between model-based approaches and learning-based techniques [12]. Our approach will also recover outstanding edges from the evolution of decoded video outlines. Obviously, the first one is used to create another DCNN for video artifact reduction under the Recursive Ensemble Particle filtration process. The key commitments of this research are two-overlap in description. To begin with, describe the reduction problem of the video artifact as a Recursive Ensemble Particle filtering method, which can recover the decoded outlines successively. DCNN is used in this approach to project and energize the filtering of Recursive Ensemble Particle filtering. Second, as solid previous evidence for video antique reduction by DCNN, use the quantized perception remaining. Trial findings show that our suggested solution beats the best for decreasing video encoding artifacts in class approaches [13].

Related Work

Dong C et. al [14] has suggested variety of methods have been suggested to remove the compression artifacts. Analysis techniques for eliminating interference and resonance artifacts have produced new detectors. One of the drawbacks of these methods is that such manually designed filters do not adequately handle the loss of encoding and can over about the decrypted objects. Learning techniques focused on sparse coding also were proposed for the removal of image artifacts. Loy C et. al [15] has suggested acquiring a minimize the cost function from a collection of training examples that are used to eliminate artifacts introduced by video frame compression. Tai Y et. al [16] has implemented the methodology by extracting information from the DCT and a sparsely based double domain approach is created. DCNN based techniques have increasingly been effectively used for low-level image analysis tasks. Zhang et al. [17] recommended eradicate artifacts from JPEG compression, he proposed the reduction of CNN artifacts. Several solutions have been introduced, inspired by CNN, to remove compression artifacts, using various techniques, such as residual learning, skip connection, batch normalization, conceptual loss, residual frame, and emergent oppositional network. Change Loy, C et al. [18] has proposed a 20-layer neural network to eliminate unknown noise levels from Gaussian noise, based on batch normalization and recurrent learning. A storage cube, comprising of a recurrent unit and a gate unit, was introduced through an effective teaching framework to explicitly mine main storage. Guo et al. [19] has proposed variety of mechanisms were implemented to recognize the object before using CNN and to generate competitive results for image analysis tasks, he suggested. In encoding code references, there are already redundancies. It is also possible to obtain a more robust estimation by using the previous knowledge found in the sequencer. Galteri et. al [20] has suggested that all of the previous works would not misuse the important prior information. Although incorporation of DCT data is indicated for the job, the function of minimizing artifacts in particular is not adequate. In our work, we further impact the previous knowledge of code origins and introduce persistent estimation into our framework for the thorough elimination of compression artifacts. Because of the performance of neural networks for texture analysis, some CNN-based approaches were also proposed for video restoration activities. Xue et al.[21] Via motion estimating for video super-resolution, he developed an SR drawn arrangement and then used a CNN model to maintain the high definition video frame from all illustrations. Tao X et al. [22] has measured low artifacts and used objects are train a CNN video incredibly model to select the appropriate points. Works are based on matching the adjacent frames by the Spatial Transformation Network (STN) as per the estimated optical low or transforming specifications and enhancing the time consistency for the SR video project. Liu D et. al [23] has suggested successful sub-pixel motion correction and quality enhancement are achieved. Modify the texture evaluation and video restoration tasks. Caballero, J et al. [24] has suggested a system of collective training and achieved state-of-the-art results for the decrease of video objects. In comparison to the methods for minimizing single image compression artifacts, the video preservation methods exploit sequential details. Foi A et. al [25] He has indicated that these methods evaluate noisy/low-resolution videos independently without considering the previous retrieved images. Consequently, they cannot improve video reconstruction performance by using more accurate spatial features. In our work, we successively preserve each object in the images using the previous retrieved frame for video artifact elimination. Although the work aims to combine the DCNN and the filter of the Recursive Ensemble Particle, it is not designed for video enhancement assignments.

SYSTEM METHODOLOGIES

Proposed Methodology

A. Deep Ensemble Particle Filter (DEKF)

To compress videos with artifact elimination, frame changing paradigm was suggested and the basic factors are two-fold. Second, from the previously preserved images, the repair process for the new frame will profit. The previously reconstructed image is supposed to be able to provide more precise temporal features compared to the original decoded image. Therefore, spatial data from previous reconstructed frames and constructs a robust high-performance video artifact removal framework. It is apparent that the dependency on previous recovered images would lead to the elimination of video objects using a complex recursive solution. More significantly, via the recursive stream, this structure offers the ability to use long-term contextual features. As we know, most of the artifact reduction methods centered on learning image artifact reduction. While in video artifact reduction or video integral gain, the data rate is used, each frame is recovered individually without taking into account the previous preserved frames. The aim is to construct a complex filtering method for high quality reconstruction to take advantage of correct spectral analysis in the given image.

The input frame $X \in R^{U \times V}$ were first filtered using DEKF. The output obtained is $Y \in R^{U \times V}$. The bilateral filtering operation is defined as

$$y[u,v] = \sum_{k}\sum_{l} R^{-1}(k,l) h_d(u,v;k,l) h_r(x[u,v], x[k,l]) x[k,l] \tag{1}$$

where $x[u,v]$ represents the input image and $y[u,v]$ represents the filtered output. Also, h_d and h_r represents domain and range filters respectively. They are represented as

$$h_d(u,v;u_0,v_0) = e^{-\left(\frac{(u-u_0)^2+(v-v_0)^2}{2\sigma_d^2}\right)} \quad (2)$$

$$h_r(x[u,v],x[u_0,v_0]) = e^{-\left(\frac{(x[u,v]-x[u_0,v_0])^2}{2\sigma_r^2}\right)} \quad (3)$$

Here $[u_0,v_0]$ represents the center pixel. Also, σ_d and σ_r represents the standard deviation of the domain and range filter respectively.

The above two equations were modified by including an offset component. Thus, the DEKF is defined as

$$h_d(u,v;u_0,v_0) = e^{-\left(\frac{(u-u_0)^2+(v-v_0)^2}{2\sigma_d^2}\right)} \quad (4)$$

$$h_r(x[u,v],x[u_0,v_0]) = e^{-\left(\frac{(x[u,v]-x[u_0,v_0]-\varsigma[u_0,v_0])^2}{2\sigma_r^2}\right)} \quad (5)$$

The sharpness of the image is controlled by ς . The image gets blurred when the value of ς is moved closer to the mean. However, by moving it away from the mean, the filtered image gets sharper.

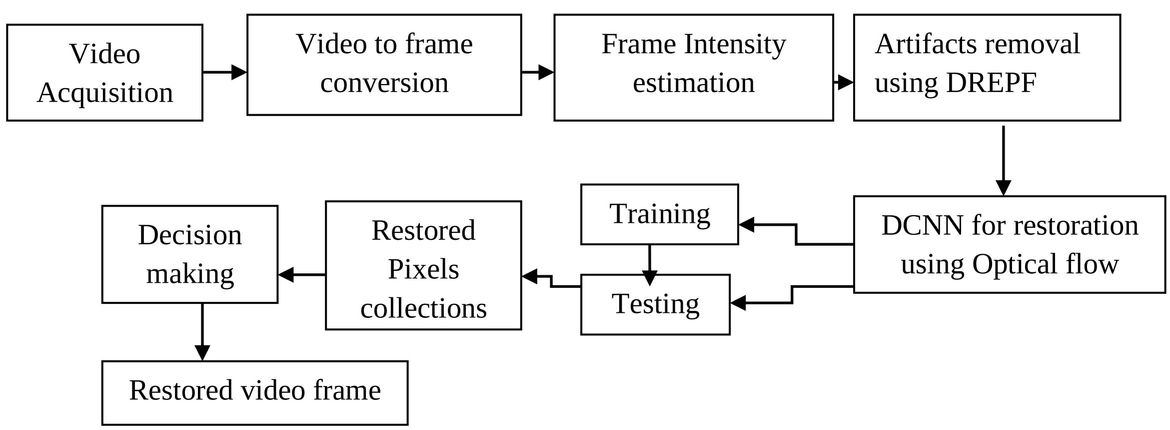

Fig.2 (a) proposed block diagram

The figure 2 (a) shows the proposed architecture diagrams. The input video is given to the process using optical flow and DCNN.

B. Video Sequence

Video sequence is an arrangement of video, audio and graphics clips on the timeline which is ready to restore frames. A frame changing sequence varies 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 propagation in videos of visible motion accelerations of intensity patterns that can provide valuable knowledge about the spatial structure of the scene and the rate of shift of artifacts. The most commonly used approaches for optical flow processing in video sequence are quantitative approaches. Among them is the Optical Flow of Lucas-Kanade, suggested by B.D. T. and Lucas. Kanade, to calculate optical flow densely for each object, is a local least square measure. Optical flow vectors derived by the Lucas-Kanade method have been extensively researched and used due to fast computing, easy implementation, and reliability under interference. The optical flow explains the specifics of each structure's motion shifts and represents the variation or resemblance of objects in image sequences. In a video environment, optical flow is the phenomenon of visible objects, lines, and edges induced by the relative movement between an individual and a scenario. There are also several methods of measuring the optical flow between two images, like variance, region-based, resource, and process methods, but quantitative methods are widely used in optical flow techniques. The system of optical flow that is predicated on the notion of consistency of illumination conditions is the quantitative process. For all particles inside a window centered at p, the optical flow formula may be expected to hold. There are more formulas of optical flow than uncertainties and hence it is typically over-determined.

D. Correlation

Coefficient, convolution and certain elements of one of the convolution implementations, image processing, are the simple picture procedures. Image differentiation and convolution are distinguished by two mere minus signs from each other but are used for various purposes. The Association formula is shown by the continuity formula, equation (1).

$$\rho_{xy} = \frac{\mathrm{Cov}(r_x, r_y)}{\sigma_x \sigma_y} \qquad \dots (1)$$

The convergent validity is confined to -1 and +1 and can be translated as follows: -1: If it is -1, then the aspects are found to be absolutely highly associated. That implies that if one variable moves in one direction, then another factor moves in the other position.

E. Duplicate Frame Identification

The fundamentals for successful identification are optical flow and their strong and reliable association in copy-move tampered images. The accuracy of optical movement is first evaluated for cost estimation purposes to locate potential interfered locations. Many estimates and comparisons of covariance matrix will help minimize the process, but can lead to further false alarms. In order to balance the overlapped frame pairs, fine identification based on optical flow similarity is then recommended, and the elimination of false region detection on validation tests can be further carried out for accuracy.

F. Unwanted Frame Removal

With irregular points in OF sum ranges, it is worth little that fine detection for copy-move forgeries relies on the delicate identification effects. Neighboring images with high resemblance can also contribute to

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false alerts in fine identification based on association evaluation. In addition, after copying, extra operations may be done, moving forgery to create disturbance and cover up the deviations.

Deep Convolutional Neural Network (DCNN) for video frame artifact elimination

The deep convolution concept of instruction also increases its capacity for extracting features and its reliability for efficient operation. Until matching, the feature learning clustering algorithm of a sample picture was retrieved using a computer program. In the suggested DCNN, to predict image quality optimization outcomes, multi-level feature vectors are trained and removed. In our strategy, high-level technologies with information dissemination are combined with low-level feature with location data to boost low-light input images.

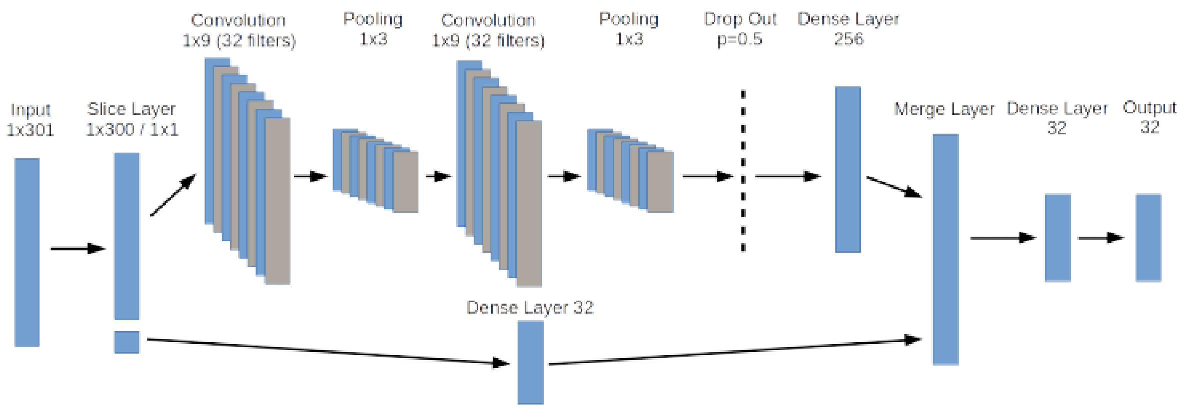


Figure 2 (b) Architecture diagram of Deep Convolutional Neural Network (DCNN)

Figure 2 (b) shows the architecture diagram of DCNN. The suggested network can efficiently spread the differential regression to the previous nodes within the network by terms of long-range residual ties and interfaces. This is of critical significance to our strategy which helps our network to achieve successful end-to-end preparation. The suggested DCNN consists of two convergent path modules: part of the forward encoder and part of the reverse decoder. A 4-cascaded network is modeled in our design, incorporating four sub-nets in the decoder section. The performance of the linked layers in the previous encoding portion is taken as input by both of these sub-networks. Furthermore the performance of the previous sub-net is also related to the sub-net below. Despite the fact that the architectures of all the sub-networks are identical, the requirements of the sub-networks are not related, allowing versatile adaptation to be carried out by each system. There have been very few experiments employing deep learning approaches for the reconstruction of pictures. For video frame de-noising and post-de-blurring de-noising, multi-layer perception (MLP), whose all levels are completely (as opposed to convolutional), is implemented. For video frame de-noising and elimination of noisy variations, the convolutional neural network has been more intimately associated to our function. Almost de-noising-driven are these reconstruction issues. On the opposite, the object super-resolution concern has not experienced to the best of knowledge the use of deep learning methods.

Create a single video frame that is low-resolution. With recurrent connections, which is really the only pre-processing we do, we first upgrade it to the required level. Denote the object resampled as Y. Our aim is to retrieve from Y an image F(Y) that is as close as possible to the elevated image X of the reality on the ground. We still label Y a "low-resolution" image for ease of viewing, while it is the identical size as X. We want to learn to map F, which comprises of 3 activities functionally:

Emission and description of positions: this procedure removes fixes from the low-resolution video frame Y (evenly spaced) and depicts each spot as a high-dimensional matrix. These formulas consist of a set of maps of features, the percentage of which is comparable to the dimensional space of the matrices.

Non-linear charting: This procedure maps each strong vector to another strong vector in a nonlinear fashion. Functionally, each mapped vector is the reflection of an elevated patch. Another set of function maps is composed of these variables.

Restoration: To produce the final elevated file, this process aggregates the above high-resolution patch-wise depictions. It is assumed that this object would be identical to Ground Reality X.

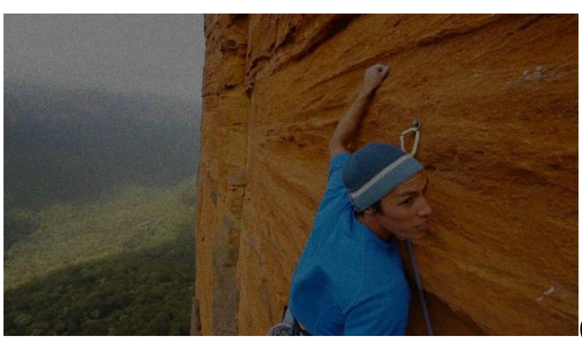
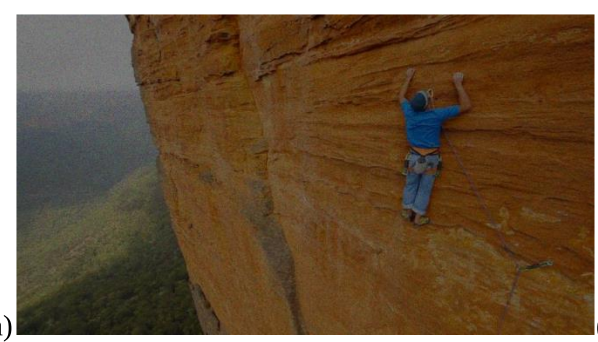
Table 2: Classification methods comparison

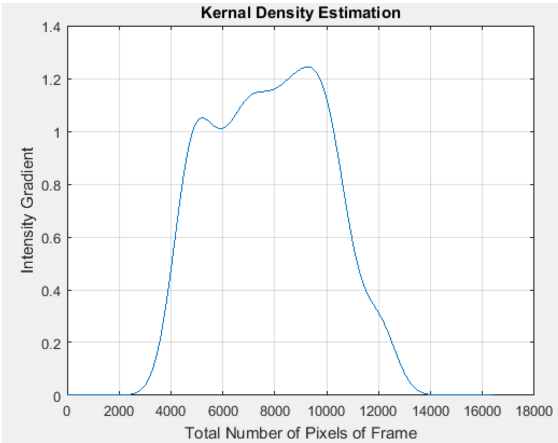
Classification	Algorithms	Precision in %	Accuracy in %
ANN	BPNN	64	69
DL	DCNN	96	97

The table 2 shows the comparison between classification methods such as Back Propagation Neural Network and Deep Convolutional Neural Network.

Results and Discussion

The proposed Recursive Ensemble Particle Filtering model-based video compression method and its operations are implemented quantitatively using MATLAB, a popular and well-known platform used by most development of digital image processing and video processing. The precision specifications are also precisely calculated and the data of all precision measurements is summarized and visualized below. Figure 3 below shows how the input video is interpreted from the file using the frame classification of the interface. The video is broken into a variety of images from the input video and the split images are collected from the main frame archive.


(a)

(b)



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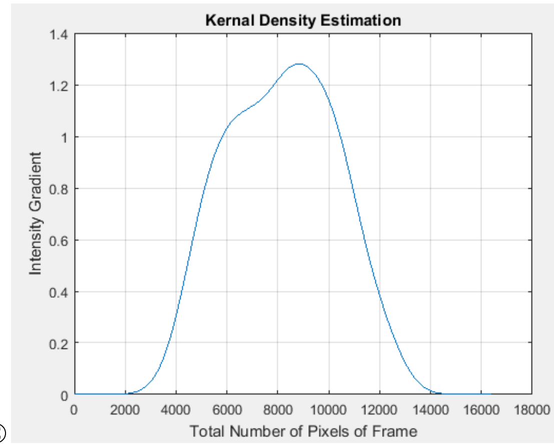

(d)

Figure 3. (a) Input video frame 1, (b) Input video frame 2, (c) Kernal density estimation of intensity gradient estimation using REPF for video frame 1, (d) Kernal density estimation of intensity gradient estimation using REPF for video frame 2.

The corresponding figure 4 illustrates the study of the optical flow based object segmentation using DCNN by contrasting the association between each pixel in the picture and each other. The split frames reflect the comparison between each frame, which is adjusted for outcome.

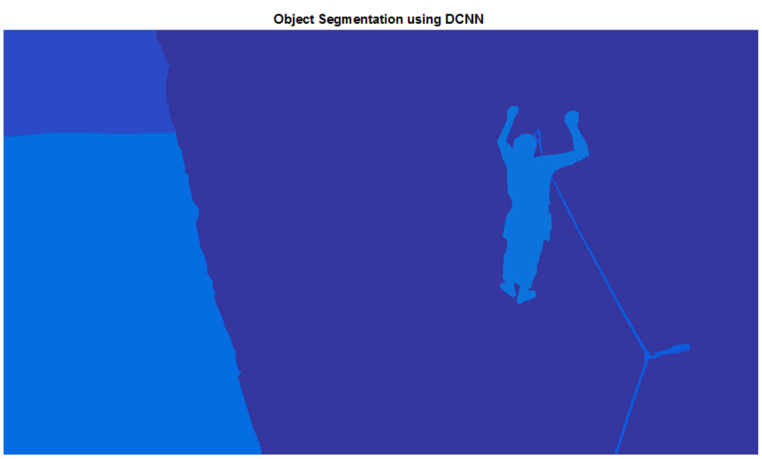

Figure 4: Object segmentation using DCNN by applying optical flow

The following figure 5 shows the output of Deep Recursive Ensemble Particle Filter (DREPF). The proposed DREPF is used to improve the video frame in terms of filtering all types of noises and quality improvement in terms of contrast and brightness.

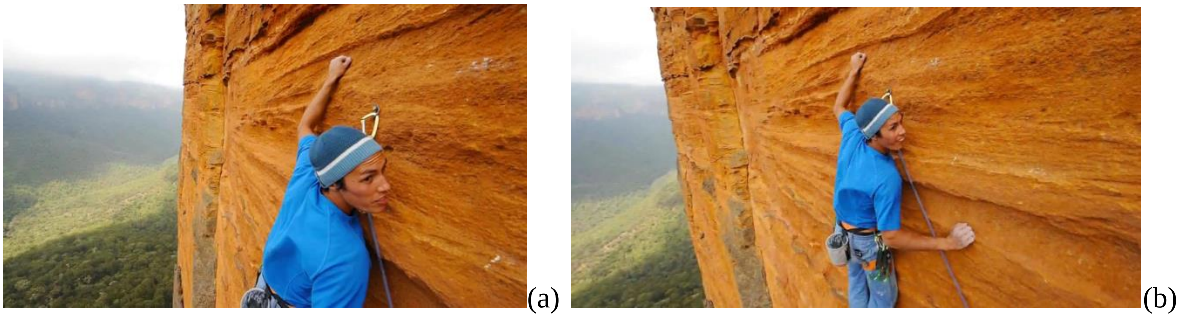

Figure 5: (a) The restored video frame 1 using Deep Recursive Ensemble Particle Filter (DREPF), The restored video frame 2 using Deep Recursive Ensemble Particle Filter (DREPF)

The following diagram shows the edges of the objects contained in the images, and then the values are slightly distinguished in the direction of x and y relative to time.

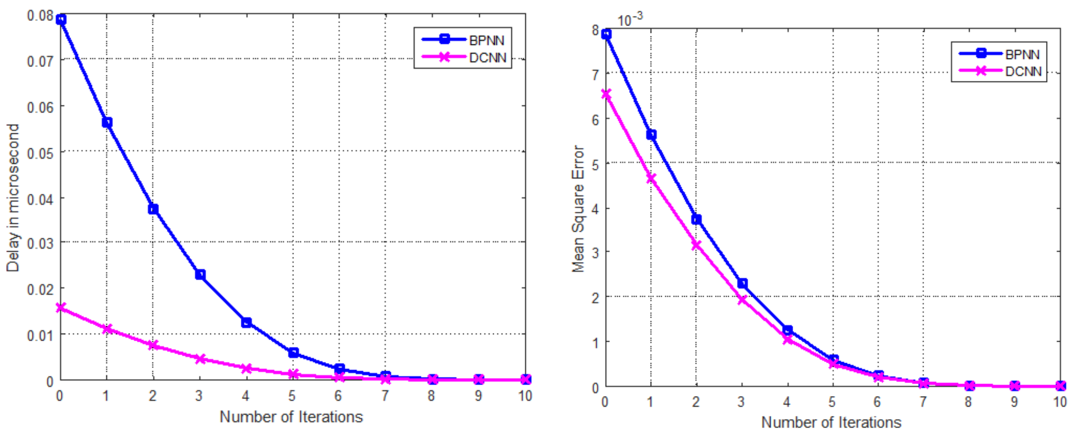

Figure 6 (a) Delay graph, (b) MSE graph

Delay Vs cumulative number of iterations of the Back Propagation Neural Network (BPNN) and DCNN are seen in Figure 6 (a). As seen in the diagram, the efficiency of DCNN is higher than BPNN. The Mean Square Error elimination using BPNN and DCNN is given in figure 6 (b). DCNN's MSE is smaller than BPNN's. DCNN efficiency is higher than current techniques, dependent on latency and MSE.

Conclusion and future work

The novel algorithm is proposed to enhance the quality of the video after compression by applying deep Deep Ensemble Particle Filter (DEKF). The quality of video is enhanced using the DEKF. The DCNN is applied to calculate the equivalent positions in the Recursive Ensemble Particle filter and incorporated equally in DEKF. The proposed framework could consider advantage of the recursive structure of both neural network potential for particle filtering and classification algorithms. The proposed network uses all the functionality and data from the encoding portion and delivers the product of high-resolution improvement in the convergence pass. Global characteristics produced by different levels are progressively fused and optimized in our model using local characteristics from previous convolution layers. In order to accommodate combined noise, a novel training impairment is further developed. The supremacy of our deep particle filtering network over state-of-the-art approaches has been shown by research observations. To handle other low-level optimization problems, such as video super resolution or de-noising, which will be researched in the potential, our approach can also be expanded in future.

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