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Enhancing Video Quality of a Compressed Video using CNN

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ABSTRACT

Compression has been a significant exploration subject for a long time, to deliver a noteworthy effect on information transmission and capacity. Ongoing advances have indicated an extraordinary capability of learning picture and video pressure. A video pressure structure dependent on spatiotemporal goal adjustment was proposed, which powerfully resamples the information video spatially and transiently during encoding, in light of a quantization-goal choice, and reproduces the full goal video at the decoder. The essential thought is to acknowledge spatial-worldly vitality compaction in learning picture and video pressure. In this way, a spatial vitality compaction-based punishment into misfortune work has been proposed, to accomplish higher picture pressure execution. Worldly up sampling is performed utilizing outline reiteration, while a convolutional neural system super-goal model is utilized for spatial goal up sampling.

KEYWORDS: Super Resolution, PSNR, CNN, Sampling, High Efficiency Video Coding.

1. INTRODUCTION

With the ever-increasing demand for more immersive visual experiences, video content providers have been extending the video parameter space by using higher spatial resolutions, frame rates and dynamic ranges. This dramatically increases the bitrate required to store and distribute video content, challenging current bandwidth limitations and demanding greater compression efficiency than offered by the current generation of video codecs. Prediction models have been developed or have been introduced the resolution adaptation as one of the rate-distortion optimized modes at a block level (CTU) but apply them for H.264 or intra coding only. Regarding temporal adaptation, a few methods for frame rate selection have been proposed in and however these have not been fully integrated with video compression algorithms. Moreover, the reconstructed video quality depends highly on the video resampling technique applied. Previous spatial resolution adaptation approaches have mostly employed linear filters, such as bicubic, for the reconstruction of full resolution video frames. However, in recent years, CNN-based super resolution techniques have become popular in the field of computer vision due to the improved reconstruction quality. Such machine learning-based approaches have however not been fully explored for video compression.

2.RELATED WORK

In this paper we worked on quality assessment and spatial resolution adaptation for intra coding, a spatio-temporal resolution adaptation framework for video

compression, which dynamically predicts the optimal spatial and temporal resolutions for the input video during encoding and attempts has been proposed to reconstruct the full resolution video at the decoder. **The main contributions of our paper include:**

- The integration of both spatial and temporal adaptation into a single framework;
- A Quantization-Resolution Optimization (QRO) module which applies perceptual quality metrics and machine learning techniques to generate reliable resolution adaptation decisions;
- The employment of a CNN-based super resolution model to reconstruct full spatial resolution content, trained specifically for compressed content;
- The integration of the spatio-temporal resolution adaptation framework for video compression framework with HEVC reference software.

3. ARCHITECTURE

The proposed framework integrates spatio-temporal adaptation with video encoding in order to maximize rate-quality performance.

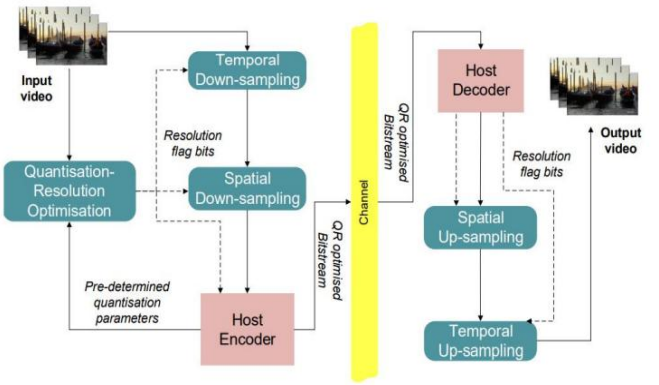

Fig 3.1:CNN Architecture

4. WORKFLOW

The steps given below are followed sequentially and PSNR before and after CNN are calculated at the final stage, by which the video quality enhancement can be derived.

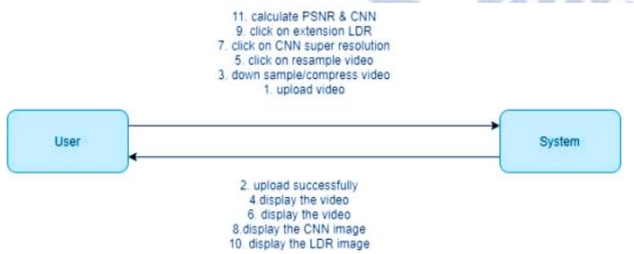

Fig 4.1: Work flow diagram

CNN with Skip Connection and Network in Network (DCSCN) a deep learning based Single-image Super-Resolution (SISR) model having 11 layers and total CNN computational filters are 10 to 100 times smaller than the others.

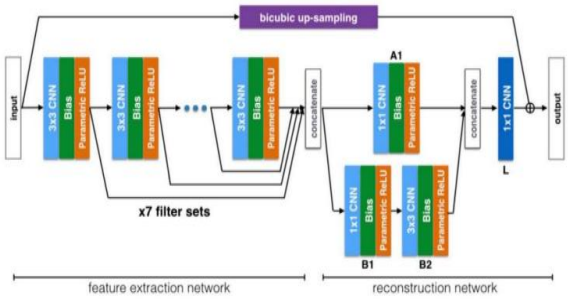

Fig 4.2:Deep CNN with Skip Connection and Network in Network (DCSCN) structure

5. RESULTS

The execution of Main.py file gets the below screen. In this screen click on 'Upload Video' button and upload video.

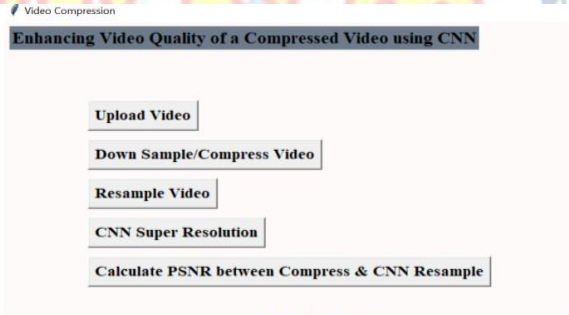

Fig 5.1: Upload video

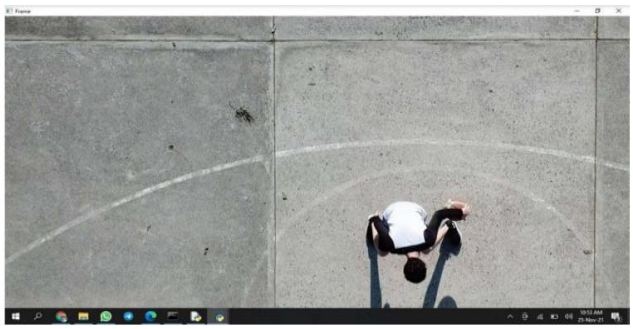

Fig 5.3: Applying compression technique

Applying compression technique to the video, here video is playing and it will run little slowly as simultaneously it is compressing also. After video playing completed then screen will automatically close and then will get below graph about video size before and after compression.

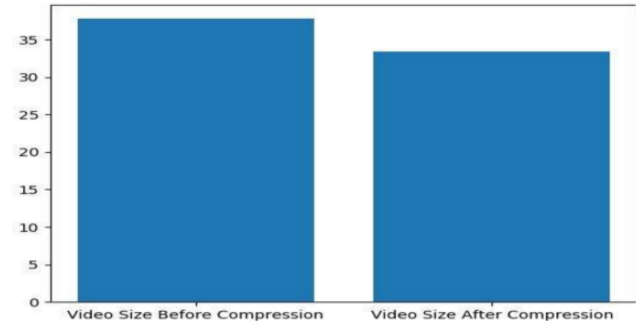

Fig 5.4: Video size before and after Compression

In above graph x-axis represents video name before and after compression and y-axis represents video size.

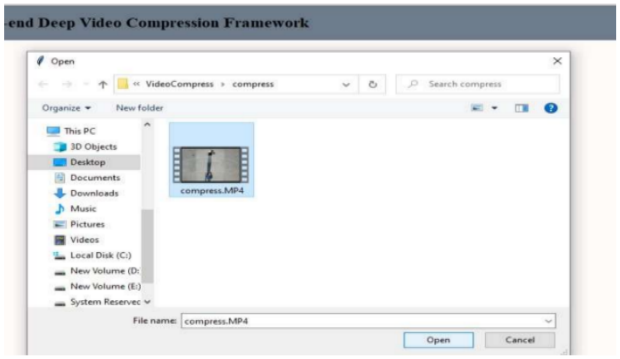

Fig 5.5:Select Compressed video

Click on the Resample video button and then select the generated compress video.

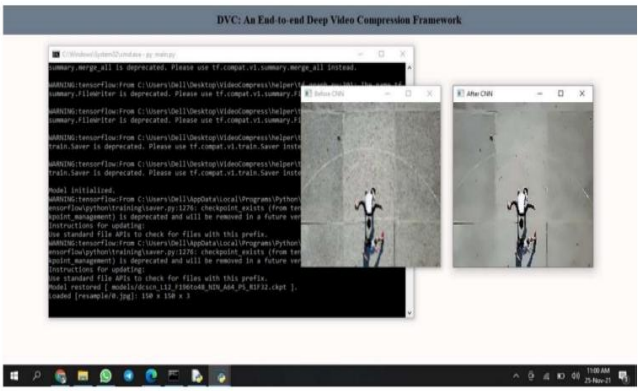

Fig 5.6:Result before CNN & after CNN

In above screen we got two images first image is before CNN and second image is after CNN. In second image you can see little clarity compare to first image.

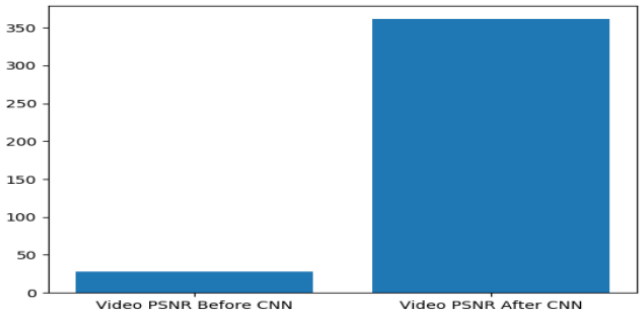

Fig 5.7:Comparing Video PSNR before and after CNN

In above graph we are getting PSNR value of video before and after CNN.

6. CONCLUSION

A spatio-temporal resolution adaptation framework for video compression has been implemented, which optimally resamples input video frames during encoding and reconstructs the full resolution video frames at the decoder. A quantization-resolution module has been proposed which computes features from the original uncompressed input video frames and determines the optimal spatial and temporal resolution at which to encode them. At the decoder, we apply frame repetition and a Convolutional Neural Network (CNN) for temporal and spatial resolution upscaling, respectively. The framework has been integrated into HEVC test model HM 16.14and extensive experimental results were conducted using objective quality metrics and subjective tests. These show that significant coding gains can be achieve by applying the proposed framework for video coding.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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