Time Dependent Video Compression For Efficient Storage

Soumya Shaw, Saurav Kumar Mishra, Sirajul Islam, Vaishanav Shukla

Abstract: The problem of digital storage is an eternal dilemma that will be there in the future as well and haunted the past researchers relentlessly. There always has been a trade-off within the choice of quality vs. quantity in all fields of life, and Digital Data storage is not an exception for sure. Our root focus will be the storage of Videos at extensive facilities that need to store colossal amounts of recording for their specific purposes. One crucial example that we would like to unravel would be CCTV footage at facilities/public places for security purposes. The footage always seems to be of bleak quality, and the details are elusive even if the incident is quite recent. This trade-off of quality sounds comprehensible since the main focus remains on having the maximum length of footage as possible. We thereby propose a time-dependent compression technique that satisfies the need of the hour. The concept suggests different levels of compression based on the age of the recorded video. The study finds the dependence of block size with the time taken for compression and, in turn, finds its performance with the help of metrics like Object Identification, Motion Tracking, Activity Recognition, and Mean Squared Error. The user is free to choose from the compression stages mentioned based on the specific application and other essential parameters like Storage capacity.

Index Terms: Compression, Compression stages, Non-linear compression, Time dependency, Time-dependent compression, Video, Video storage

1 INTRODUCTION

Videos play a crucial role in the modern pragmatic world of the 21st century. The uses are ingrained in the needs of the time. Surveillance is one of the applications of the footage recorded among the many. The storing of the data becomes impelling in such cases, and historical evidence will not deny the fact as well. But, the problem of storage once again looms up against the need and cost trade-off as a study [1] suggests a CCTV footage at low quality can gen- erate about 10 GB of data in a single day and the calculation grows obscure when multiplied by 245 million CCTV cam- eras [2] around the globe. With this example, the need for Video storage optimization prevails in front of us, wherevideo compression is the pivotal answer we are focusing on. But, simple compression is too mundane to be out there to solve the video storage issue without subsuming the con- gruous needs. The CCTV cameras are already infamous for poor video quality it elicits at the cost of lesser storage space it takes, making it possible to store the footage for a longer time. But, the pattern for storage we recommend is slightly dif- ferent and much more profound, taking care of the footage usability. The importance of the video diminishes with time and points to the fact that if it had some useful incident recorded, then the authorities would ~~have looked/requested it already, soon enough.~~

- Soumya Shaw, B. Tech, Electronics & Communication, Vellore Institute of Technology, Chennai, 600073, Tamil Nadu, India
- Saurav Kumar Mishra, B. Tech, Electrical and Electronics Engineering, SRM Institute of Science and Technology, Chennai, 603203, Tamil Nadu, India
- Sirajul Islam, B. Tech, Engineering and Technology, Kaziranga University, Jorhat, 785006, Assam, India
- Vaishanav Shukla, B. Tech, Computer Science and Engineering, Sir M Visvesvaraya Institute of Technology, Bengaluru, 562157, Karnataka, India

The older it gets void of its demand, the more it refers to the presence of unnecessary details to store. On the other hand, the footage deserves higher quality during its first few days/weeks, in- dicating to the same fact we mentioned above, any conse- quential event happened that requires attention should en-compass more top quality than usual. The supplementary quality added to the conventional quality may lead to the accurate unraveling of few factors and revving up of the progress significantly.Hence, we feel that the video quality must not be stored starkly without any necessary algorithmic optimizations. We suggest a non-linear time-variant compression tech- nique that satisfies the necessities word to word.

2 ALGORITHM DEMONSTRATION

Two standards can be followed to define the stages of com- pression i.e., Linear & Non-linear. We concentrate on the usage of Non-linear stage division for our exhibit. So, the following demonstration includes four stages of compres- sion supplemented with four intervals of non-linear time intervals, described according to the table below.

TABLE 1
STAGES OF COMPRESSION

Time Interval (in weeks)	Compression
Stage [0, 3)	Stage 0
[3, 9)	Stage 1
[9, 23)	Stage 2
[23, 52]	Stage 3

The criteria [3] [4] can be mathematically represented with

$$y = y_{max} \frac{\log_e[1 + \mu(|x|/x_{max})]}{} \mathrm{sgn}(x) \qquad (1)$$

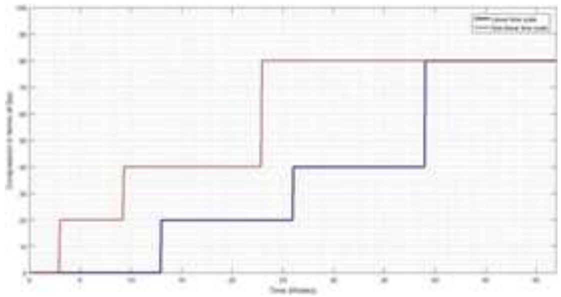

***Fig. 1**. Division of Compression Stages*

Transform (DCT) [8] [9], and it works on square matrices only. Hence, the frame must be divided into squares of spe- cific pixels. We saw that the computational time required for compression largely depend on the block size we took for DCT. The relationship is demonstrated in the graph be- low (Figure 2).Fig. 2. Effect of Block Size on Computational Time

$$\log_e (1+\mu)$$

In turn, applying the greatest integer function on the resul- tant sequence will precisely provide us and the system the compression it needs to achieve, to store it optimally taking care of the conditions. With μ = 20, we get the following pattern of Compression in Figure 1.

3 COMPUTATIONAL ANALYSIS

Our compression algorithm had the usage of a lossy com- pression technique [5], [6], [7], namely Discrete Cosine putational analysis with the block size. On the other hand, the fact is prescient that decreasing block size will elicit bet- ter video quality after decompressing it. So, there's always a dilemma to hand-pick a single extreme feature or hang in between both.

4 PERFORMANCE EVALUATION

Our time-dependent non-linear compression technique in- troduces three new stages of compression over the conven-tional approach and this addition needs further study of stages. The usability of processed data is vulnerable since the whole point of making it efficient is tied with similar re- sults. We have listed some parameters that we used for the assessment of the quality of video after extracting it back from Compression.

1. Object Identification
2. Motion Tracking
3. Activity Recognition
4. Mean-Squared Error

4.1 Object Identification

The Object Identification [10] analysis tested a standard model of Object Identification using a pre-trained Deep Learning model to predict the object in the frame of a par- ticular video provided. The first image (frame) had a cake in it, although the second consisted of a food item. The out- comes of the analysis are tabulated below.

TABLE 2

Prediction Accuracy

Qac	Prediction 1	Certain- ity	Prediction 2	Certain- ity
-	cake	64 %	food	81 %
10	cake	62 %	food	78 %
20	cake	62 %	food	78 %
40	cake	66 %	food	78 %
80	cake	58 %	food	77 %
160	handbag	76 %	food	76 %

We witness the trend of the inverse relationship of com-
This unravels the point that there is no significant change. However, a minute decreasing slope of accuracy until the compression is too high where the prediction model identi- fies it wrong in one of the cases

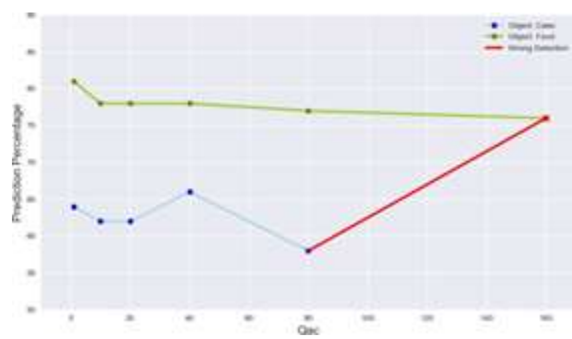

Fig. 3. Object Identification

4.2 Motion Tracking

The Motion Tracking [11] ability is tested with the Back- ground Subtraction algorithm. It assesses the centroid of the moving patch in turn. The comparison of other video qualities includes the mean positional error of the resulting centroid that is tracked. It is expressed in Figure 4.

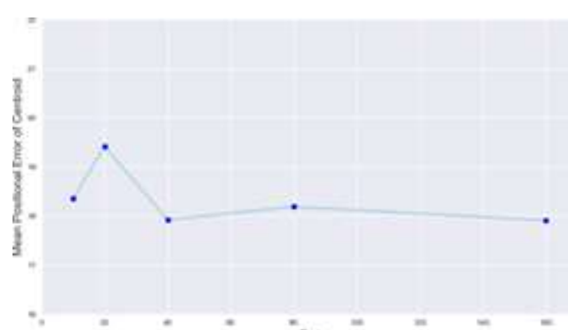

Fig. 4. Motion Tracking

Motion Tracking tolerates the noise introduced during Compression as well and proves to be very much unaffected. If we carefully look at the concept behind Motion Tracking, the presence of blurring is pivotal and an essential step. The blurring caused by Compression turns out to be ephemeral in such ituations.

4.3 Activity Recognition

The Action Recognition model [11] tries to predict the action being performed in the video clip based on a pre-trained Tensorflow Deep Learning Model. The output of the model is in the form of the top three predictions of actions that closely resembles the training categories. The testing is done on two different kinds of videos, one being HD and the other being a normal one. The trend for the prediction follows two inferable patterns. The HD quality video shows no such drop in prediction accuracy even when the compression on the video is substantially increased. On the other hand, lower video quality shows a decreasing trend of the accuracy of Rank 2 & 3 prediction confirms the fact that the model struggles to understand the action with increased compression and confuses with other activities.

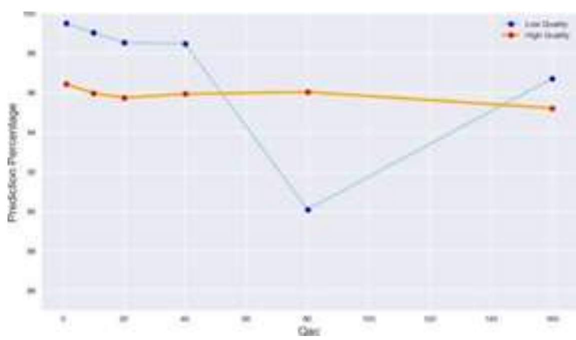

***Fig. 5**. Prediction Rank 1*

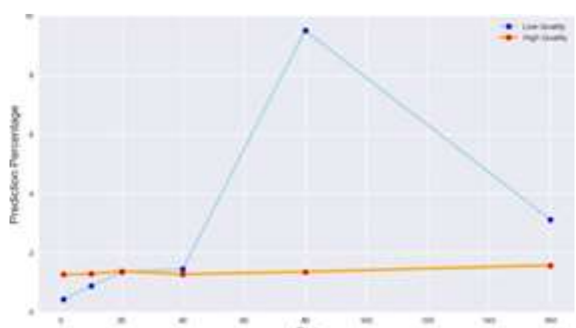

***Fig. 6**. Prediction Rank 2*

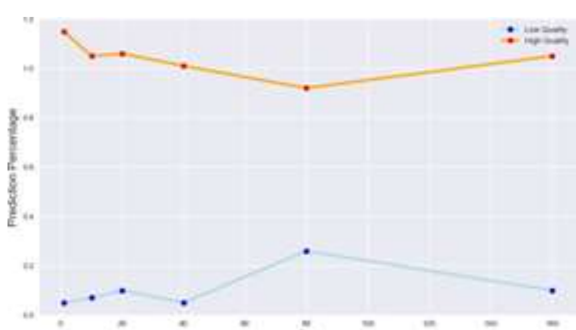

***Fig. 7**. Prediction Rank 3*

4.1 Mean-Squared Error

The Mean Square Error [12] works pretty much the same as we know. However, instead of calculating the error of two different pixel values of respective imag- es, it works on two different pixels of varying video frames. Hence, the conversion of video frames into grayscale is followed by finding their MSE, frame by frame between original uncompressed video and com- pression retrieved videos and terminating by avera- ging the whole sequence of mean squared error. The result is as follows, given in Figure 8.

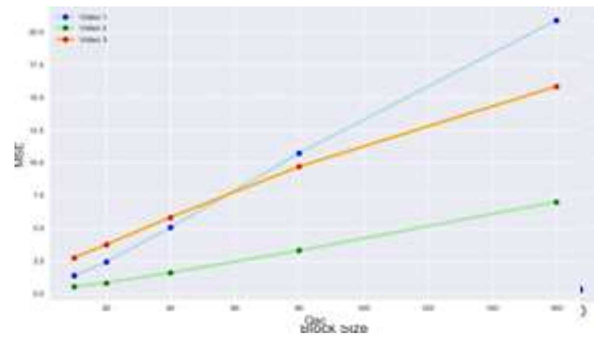

***Fig. 8**. Mean Squared Error*

The three test videos pristinely point towards the in- crease of values with increasing compression that can be tightly fitted to a linear slope. Apparently, videos with higher quality elicit a lower slope of MSE.

CONCLUSION

Our technique will solve the transcending problem of Video storage ephemerally, where the future advance- ments will come into play. The study gives various insig- hts into the field of Time-dependent video compression technique, adding another startling paradigm of Non- linearity in it. The user has an option to pick from linear and non-linear nature based on its applications, both being equally handy. There must be a selection of stages based on the applica- tion and level of usage required after storage. The perfor- mance analysis provides a path out of the dilemma for the implementation.

FUTURE WORK

The future work for the concept will be primarily based on the fact that how other complex Video compression techniques will perform with the Time-Dependent Com- pression idea and check its compatibility. Since we have used the Lossy compression procedure, the use of Loss- less compression algorithms [5] like Run Length Encod- ing, Lempel-Ziv-Welch and Huffman coding will also be a field of study for future enthusiasts. Modern techniques like H.261, H.263, H.264 can be studied along with hybrid DWT-DCT algorithm. [14], [15] The future progr- ess of applying better compression techniques will be able to annihilate the storage problem and reduce the burden on the revamping need of Technological advance-ment.

REFERENCES

[1] D. Suganya, R. Shyla, V. Jayasudha, and S. Mari- rajan, “Storage Optimization of Video Surveilla- nce from CCTV Camera,” International Research Journal of

Engineering and Technology (IRJET), vol. 5, no. 3, pp. 1356–1359, Mar 2018.

[2] Video Surveillance and Storage Survey by IHS Technology," Sep 2014.

[3] V.N. Sonawane and P.S.V. Khobragade, "Comparative Analysis between A-law & µ-law Compand- ing Technique for PAPR Reduction in OFDM," International Journal of Advanced Research in Computer and Communication Engineering, vol. 2, no. 5, May 2013.

[4] V. Tejaswini and K.U. Chowdary, "PAPR Reduction in OFDM using SQRT and Mu-Law Companding Techniques," International Journal of Engineering Development and Research (IJEDR), vol. 5, no. 3,2017.

[5] N. Devi, V. Singh, and V. Thakur, "A Study of Dif- ferent Video Compression Techniques and Latest Standard," International Journal of Trend in Research and Development, vol. 4(3), May-Jun 2017.

[6] M. Singh, S. Kumar, S.S. Chouhan, and M. Shrivastava, "Various Image Compression Techniques: Lossy and Lossless," International Journal of Computer Applications, vol. 142, no. 6, pp. 23–26, May 2016.

[7] P. Kavitha, "A Survey on Lossless and Lossy Data Compression Methods," International Journal of Computer Science Engineering Technology (IJCSET), vol. 7, no. 3, pp. 110–114, 03 Mar 2016.

[8] M.M.S. Rani, P. Chitra, and K. Anandharaj, "A Stu- dy of Various Video Compression Techniques," in 5th National conference on Computational Methods, Communication Techniques and Informatics (and others, ed.), vol. 1, 2017.

[9] T. Aziz and D.R.J. Dolly, "Motion Estimation and Motion Compensated Video Compression Using DCT And DWT," International Journal of Emerging Technology and Advanced Engineering, vol. 2, no. 12, pp. 667–671, Dec 2012.

[10] P.K. Mishra and G.P. Saroha, "A Study on Video Surveillance System for Object Detection and Tracking," 3rd International Conference on Computing for Sustainable Global Development, pp. 346–351, Mar 2016.

[11] K.N.A.K. Nihal, "Research Inferences In Video Compression Domain," International Journal of Engineering and Advanced Technology (IJEAT), vol. 8, no. 6, pp. 3659–3665, Aug 2019.

[12] S.S. Wadd and P.S.B. Patil, "Video Compression Using DCT," International Journal of Advanced Rese- arch in Computer Science and Software Engineering, vol. 4, no. 9, pp. 394–398, Sep 2014.

[13] D.S. Choudhary and P. Varshney, "A Study of Digital Video Compression Techniques," Paripex Indian Journal of Research, vol. 5, no. 4, April 2016.

[14] L.E. Tresa and D.M. Sundararajan, "Video Compression Using Hybrid DWT-DCT Algorithm," International Journal of Emerging Technology and Advanced Engineering, vol. 4, pp. 918–922, 2014.

[15] S.V. Phakade, H. Patil, and S.K. Nikam, "Video Compression Using Hybrid DCT-DWT Algori- thm," International Research Journal of Engineering and Technology (IRJET), vol. 3, pp. 2758–2761, 2016.

AUTHOR BIOGRAPHY

Soumya Shaw is currently studying his B.Tech in Electronics & Communication in the Vellore Institute of Technology, graduating in 2021. He is an IEEE member and interestingly working on Deep Learning, AI, Image Processing. Besides, he is overzealous in the field of Cosmology, Higher Dimensional Mathematics & Quantum Mechanics.

Saurav Kumar Mishra is currently pursuing his B.Tech in Electrical & Electronics Engineering from SRM Institute of Science and Technology, graduating in 2021. He is an IE(I) SRM Local centre member and is working on Semi Z Source converter (DC-DC), Inverter, PWM Techniques for Sing- le phase Inverter Technology. His interest lies in MATLAB & SIMULINK, NI MULTISIM, Arduino Simulations and Circuit designing.

Sirajul Islam is currently pursuing his B.Tech in Electronics & Communication at Kaziranga University, graduating in 2021. He is passionate about MATLAB simulation, VLSI, Big Data, and Image Processing.

Vaishanav Shukla is currently doing his B.Tech in Computer Science and Engine- ering at Sir M V Institute of Technology and will be graduating in the year 2022. He is always excited about new tech and product development and wishes to learn and work in the field of AI and ML. He has a keen intere- st in theoretical physics as well.