ISSN: 0976-9102 (ONLINE)
DOI: 10.21917/ijivp.2024.0469

DESIGN AND ANALYSIS ON IMAGE COMPRESSION USING NEURAL NETWORKS

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Abstract

Due to the explosion of video based information proliferating in the world due to the ubiquitous usage of video cameras the amount of video based information that is currently being generated around the world is huge. And due to security purposes it is becoming imperative that these video data needs to be stored in computer memory for an extended period of time for referrals by security agencies. Because of the advancement of imaging technologies that is being used nowadays it is possible to capture extremely detailed high definition images. But it is not physically possible to store all these high-definition images in computer memories for a long time because infrastructure providers will run out of memory. Image compression is a technology which assists us in this regard. Nowadays this technology has moved from image compression to video compression to compression of 3-dimensional videos which is now becoming more and more popular due to the ever increasing usage of Augmented Reality, Virtual Reality and Ec The quantity of image data produced in modern surveillance networks is rising exponentially year on year which necessitated development of novel schemes for reducing the sizes of the images captured by CCTV cameras while not compromising on the image quality increases when the images are decompressed. This paper proposed a novel Deep Neural Network based method of compressing images in which the image accuracy is not lost but the space it occupies in the memory storage of the computes is reduced greatly compared to other image compression schemes, this proposed scheme is best suited for usage in CCTVs and other networks using Internet of Things which record images and videos continuously.

Keywords:

S-BHM, Slimming Encoders, Image Compression

1. INTRODUCTION

In recent years, the rapid proliferation of digital media and the ever-increasing demand for high-resolution images have underscored the critical importance of efficient image compression techniques [10]. Image compression plays a pivotal role in various applications, spanning from multimedia content delivery to medical imaging and surveillance systems [11]. One particularly crucial application is the use of image compression in Closed-Circuit Television (CCTV) cameras deployed for monitoring road traffic, which has become instrumental in ensuring safety, traffic management, and law enforcement on roadways [12].

CCTV cameras along roadways have become an integral part of modern traffic management and security systems [13]. These cameras capture vast amounts of visual data round the clock, generating substantial storage and bandwidth requirements. Efficient image compression [1]-[5] in this context is not only desirable but often indispensable to facilitate real-time monitoring, archival storage, and data transmission [14].

The successful deployment of CCTV systems relies heavily on the ability to strike a balance between reducing data size and preserving essential details within the compressed images. Over the period from 2017 to 2023 [6]-[9], significant advancements in image compression have addressed the specific needs of CCTV cameras in road traffic surveillance. Researchers and engineers have been tasked with optimizing compression algorithms to cope with the demands of high-resolution video streams generated by these cameras [16]. This paper provides a comprehensive overview of recent developments and trends in image compression during this crucial timeframe, with a specific focus on the challenges and solutions pertinent to CCTV cameras in road traffic applications.

Researchers have explored a wide array of techniques, including traditional transform-based methods like Discrete Cosine Transform (DCT) and emerging approaches such as deep learning-based compression, tailored to the unique requirements of road traffic surveillance. These advancements have not only improved compression ratios but have also aimed at enhancing the interpretability and utility of compressed images in critical decision-making scenarios.

Furthermore, the integration of Artificial Intelligence (AI) and machine learning has played a pivotal role in refining image compression algorithms for road traffic monitoring. These techniques enable the automatic detection of traffic incidents, anomalies, and the extraction of valuable information from compressed video feeds, thereby augmenting the functionality of CCTV systems.

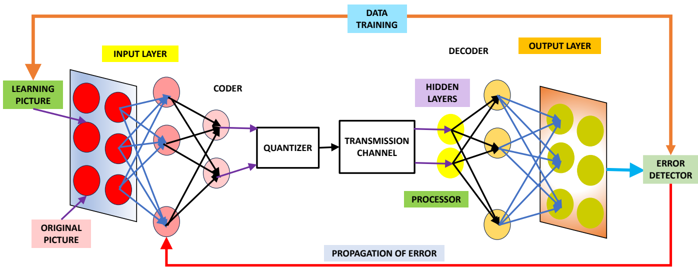

Fig.1. Codec in the basis of Neural Networks

This paper aims to provide an exhaustive survey of the noteworthy research contributions, emerging trends, and challenges related to image compression from 2017 to 2021, with a particular emphasis on its relevance to CCTV cameras employed in road traffic surveillance. We categorize and discuss the advancements in compression techniques, including lossless and lossy methods, while also examining their applications in this critical domain. In the subsequent sections, we delve into the specific methodologies, evaluation metrics, and practical considerations that have shaped image compression for road traffic CCTV cameras.

2. ADVANCEMENTS ON PICTURE COMPRESSION ON THE BASIS OF NEURAL NETWORKS

In this section, we will be discussing the literature that we have consulted that have inspired us to identify this problem related to the compressing of digital pictures that is taken by CCTV cameras in heavy traffic conditions.

2.1 CODING OF DIGITAL PICTURES ON THE BASIS OF PERCEPTRON OF MULTIPLE LAYERS

Multiple layer perceptron is made up of incoming layers of neurones or node where multiple layers of neurones are kept concealed while the ultimate layers of neurones are kept as outputs. In the multiple layers of perceptrons the outputs which are represented by the symbol h_i in which the index I stands for each neurones under considerations, that is defined by the equation presented below in the form of Eq.(1).

$$h_i = \sigma\left(\sum_{i=1}^{M} w_{ji} x_i + c_j\right) \tag{1}$$

In which the symbol $\sigma(.)$ represents the function of activation and c_j represents the term representing bias for the transforms that are linear and the terms w_{ji} denotes the parameters which can be adjusted according to the needs of the problem of compressing of digital pictures. This term w_{ji} which is also named as weight is used for representation of the relation in between layers of the convolutional neural networks. Through theoretical analytical framework in can be sufficiently proven that the perceptron of multiple layers may be built by the utilization of non-singular concealed layers and to a very high level of accuracy may give the approximated values to obtain any functions which may be calculated [17] (see Fig.2).

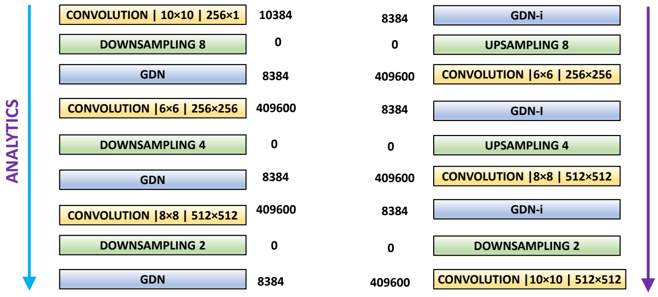

Fig.2. Parameters

2.2 CODING OF DIGITAL PICTURES ON THE BASIS OF NEURAL NETWORKS THAT IS RANDOM

By the usage of parallel networks in high definition images in the year '88 Lin and Chua made the proposition for a frame work of images from one end to the other end and with the aid of extremely strong compactness to enable neural networks representations [15]. In case of networks of neurons, a novel randomized neural network have been brought into being [17]. Unlike the multiple layered perceptron approach the network of randomized neurons act in a very unconventional manner because in the case of multiple layered perceptron signal is in the space domains and optimization of these signals is done by the help of methodologies of propagating backwards. A methodology of propagating backwards is a type of process in which the parameters are altered by updating them repeatedly and this is implemented through the solution of m number of equations that are linear in nature and through the solutions of p number of equations that are not linear in nature if one has to evaluate a pair of output and inputs.

Few scientists involved in the research of compressing digital images have brought into consideration the combining of randomized network of neurones with the process of compressing of images and have reported amazing outputs. Gelennbe et al. [18] have presented the applications of randomized neural networks in works regarding digital picture compressing. In that works the researcher have given us a decoder-encoder strategy that is constructed on the top of a randomized neural networks and in which there will be another layering of neurones placed in the middle as the concealed layer.

The Eq.(2) and Eq.(3) stands for representation of stages that have to be pursued in order to perform effective compressing of digital images which have resolutions on the higher side and this is done through the utilization of coefficients of coding that have undergone quantization and coefficients of coding that are binary in nature. Doing this we present this problem as an integrated problems of optimizing the compression coefficients.

$$p_{l,k} = \left\| X - \hat{z}_{lk} u_l^T u_l \right\|^2 \tag{2}$$

$$\hat{z}_{lk} = \left(t_1 3^{-1} + t_2 3^{-2} + \ldots + t_{lk} 3^{-c_{lk}}\right) - n_{l,k} \tag{3}$$

In the above Eq.(2) and Eq.(3), the variable mentioned as $\hat{z}_{lk}$ is a binary variable. It represents the coefficients of transforms that have been reconstructed. The variable represented by the symbol u_l denoted the kernels of transform that maintains their orthogonality. The series of variables denoted by the vector $\{t_1, t_2, t_3, \ldots, t_{lk}\}$ are in reality stand for the representation of the codes that are binary in nature and are the representation of the levels of quantization for the variable that have been mentioned d above as $\hat{z}_{lk}$. The problem of optimization (see Fig.3) that have been presented in the form of Eq.(2) has been solved by the researcher through the procedures of decisions/decomposition or neural networks.

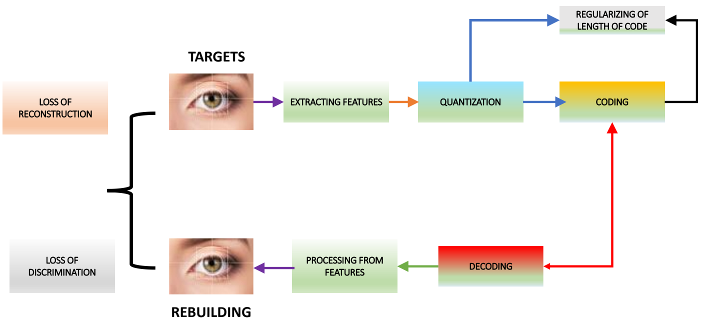

Fig.3. Overall architecture of GAN based image compression

By this process the best possible code of binary nature are secured that produces result in the form of a stream of bits which are compressed.

$$y_m = \sum_j x_j y(m-j) + \sum_j \sum_k x_{jk} y(m-j) y(m-k) + \sum_j \sum_k \sum_l x_{jk} y(m-j) y(m-k) y(m-l) + ... + \epsilon_m \quad (4)$$

For extended improvisation of the above mentioned procedures of randomized neural networks Manikopoulos used a model of predicting of high level as demonstrated by the above mentioned Eq.(4). It has been aptly demonstrated that it is using a model of automatic regression, and this methodology is able to identify accurately that if there are any edge prevalent in the digital picture.

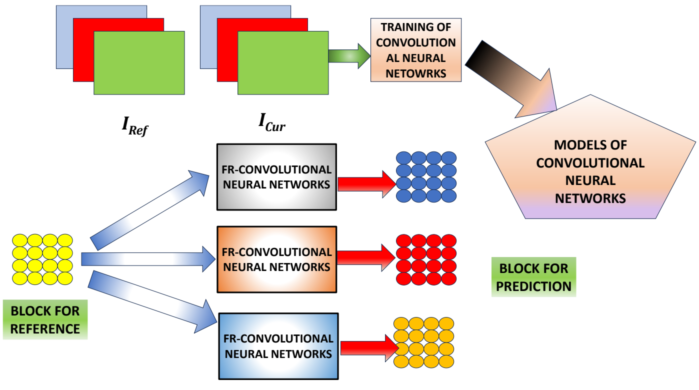

Fig.4. Framework of FRCNN in [85]

The process of another study has been conducted to research on the topic of video coding by utilizing the most utilized standard of coding videos i.e. HEVC also known as High Efficiency Video Coding has been under intensive research for the purpose of finding newer procedures of digital picture compression in the recent times. All sub-divisions of the high Efficiency Video Coding technique have been it improvises through the application of Deep Learning methodologies. Through this part the review of the works of coding videos have been undertaken based on models of learning based on 5 most important modules of video learning. One of the Most practiced techniques of coding of videos to enable compression of video data is the methodology of predicting internally through the utilization of the neural networks. In Table.1, the presentation on the performance of coding for video data have been presented through the instances of the symbol "*L*" which denotes light and through the symbol "*D*" which means duality. These are necessary for the training's of the models named in the table as Convolutional Neural Network-B/I/P against 16.9-HM. It has been found that the predicting of the interior chromatic and the rebuilt luma blocks are utilized for the improvement of the coding efficiencies for video signals. Besides they are also able to separately identify the contour or boundaries between different color regions in the image in a very successful method. In Eq.(4), the symbol ϵ_m denotes the series of independent randomized variable what have zero as their average value.

3. CODING OF DIGITAL PICTURES ON THE BASIS OF CNNS

Usage of CNN for the purposes of compressing of digital pictures have led to the event of outperforming of conventionally used approaches of compressing of digital pictures by a huge gap and this process is now being extremely widely brought under usage for works related to classifying of digital pictures and detecting of items etc. [19] as in Fig.4. For minor quality works on computer visions, for example higher resolutions and compressing of images of artifacts, the concepts of convolutional neural networks is used in this research and have used in a massive manner. Through the utilization of convolutional neural networks adoption of operations related to convolution and subsequent research on characterizing relationships between adjoining pixels around one target pixel is carried out. This is done is such a method that the properties related to the statistics of the proposed image and its pixel values stay intact.

$$w_j^{(l)}(n,p) = \sum \left(Q_{l,jk} * v_k^{(l)}\right)(m,n) + c_{k,i} \quad (5)$$

For performance of the optimization function related to the image compression process convolution of the affine process is represented in the Eq.(5). The (n,p) represents the coordinate of the pixel in the digital picture and the (*) denotes the process of convolution applied in two dimensions. The symbol $Q_{l,jk}$ is said to represent the parameter of the convolution process. Following this procedure the downsampling of the results of the convolution process is implemented by the Eq.(6).

$$x_j^{(l)}(n,p) = w_j^{(k)}(t_l n, t_l p) \quad (6)$$

In this Eq.(6), the symbol is introduced for representation of the factors used in getting the output down-sampled.

In the end the data which have undergone down-sampling undergoes processing through a transform of divisive normalization which is generalized. It is expressed in the Eq.(7).

$$v_j^{(l+1)}(n,p) = \frac{x_j^{(l)}(n,p)}{\sqrt{\gamma_{l,j} + \sum_k \delta_{l,jk}\left(x_k^{(l)}(n,p)^2\right)}} \quad (7)$$

where in the Eq.(7), the terminologies represented by the symbols $\gamma_{l,j}$ denotes the expressions for biasing terms and the terminology represented by $\delta_{l,jk}$ represents the terms of scale evaluation to normalize the procedure.

SEQUENCE	Convolutional Neural Network-B/I/P against 16.9-HM		DIRECT VIRTUALS REF. FRAMES	
	RANDOM ACCESSES	DELAY LOW B	RANDOM ACCESSES (HM-16.9)	RANDOM ACCESSES (JEM7.1)
Type 1	-2.6%	-1.9%	-7.5%	-2.1%
Type 2	-3.0%	-2.2%	-3.7%	-0.9%
Type 3	-2.7%	-1.1%	-3.7%	-1.2%
Type 4	-3.6%	-0.8%	-6.1%	-0.9%
Type 5	/	-3.1%	/	-1.1%
Considering All	-3.2%	-1.9%	-4.7%	-0.8%
Time for Encoding	151%	189%	137%	123%
Time for Decoding	4536%	2911%	4401%	1002%

Fig.5. Performance Analysis

4. CONCLUSIONS

In a collaboration with compression the visions of computers and men is one of the solutions to reach necessities of communications by visual means for Internet of Things networks. Because of being extremely complex and inefficient the solutions that propose image compression while not able to maintain the structural features of the digital image which is being compressed many of the existing schemes fail in achieving all the objectives that this

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