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Color Image Compression: Survey and Discussions

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Abstract-*Image compression is a fundamental problem in computer vision and image processing. With the development and popularity of high-quality multimedia content, lossy image compression has been becoming more and more essential in saving transmission bandwidth and hardware storage. In image compression system aims to jointly minimize both the compression rate and distortion of an image and also enhanced the quality of an image. In this paper we present the review for the image compression techniques and standards.*

Keywords:- Image Processing, Image compression, JPEG, JPEG 2000, Image classification.

Introduction

Image compression has been an significant task in the field of signal processing for many decades to achieve efficient transmission and storage. Classical image compression standards, such as JPEG and JPEG2000, usually rely on hand-crafted encoder/decoder (codec) block diagrams. Along with the fast development of new image formats and high-resolution mobile devices, existing image compression standards are not expected to be optimal and general compression solutions [7]. Compression methods can be split into two categories: lossless (e.g. PNG) and lossy (e.g. JPEG).

While lossless methods provide the best visual experience to the user, lossy methods have an non-invertible compression function but can achieve a much higher compression ratio. They often come with a parameter to span the trade-off between file size and quality of the decompressed image [9]. Nowadays, as a common and effective information carrier, a color image has penetrated into every corner of social life, which leads to our increasing demand for image processing, e.g., color image classification or color image forensics.

Classification techniques enable computers to replace human beings to complete classification tasks. Forensics technology ensures the security of image information. In real life, most color images are stored in JPEG format. If an image is tampered with, it will undergo decompression, and then compressed to form a double JPEG compressed image [3]. Therefore, double JPEG compression is an inevitable process in image tampering. Detecting double JPEG compression provides strong support for image forensics. No matter the color image classification, the essence of them is to extract the features of the color images, and to classify the images by effective features. Hence, a model that can extract effective features is crucial for various image processing tasks.

Despite their high performance on gray-scale images, DCT domain-based methods typically suffer from handling color images for two main reasons. First, because the entire network is a highly nonlinear system, simple linear operations on input images would lead to unpredictable nonlinear outputs. In other words, using methods developed for gray-scale images to recover color images by restoring each color channel separately would lead to chromatic aberrations. Second, because the compression algorithm for the luminance channel differs from that for the two chrominance channels, using a single model trained for the luminance channel to recover two chrominance channels would produce undesired results [1].

Currently, JPEG compression is a popular compression standard. Therefore, the forensic issues related to JPEG format receive more attention. Besides, many forensics techniques related to videos. If a part of the source JPEG image is moved into a target JPEG image, the target image which is called the tampered image will save again which results in double JPEG compression. Many research works have been done to detect double JPEG compression [6].

There are still some methods designed for detecting double JPEG compression with the same quantization matrix. As the number of compressions increases, more and more JPEG coefficients changed to zero, which means that there would be fewer different JPEG coefficients between the twice compressions. Therefore, the threshold selected by author was set to distinguish double compression JPEG with the same matrix [6].

II. JPEG/JPEG 2000

JPEG [8] is one of the most commonly used algorithms for lossy image compression. In this study, JPEG will therefore be the reference to compare the performance of encoders. JPEG can typically achieve a compression ratio of 10 with smalls perceptible loss in image quality [8]. The algorithm is particularly efficient on images with smooth variations of color, like photographies. JPEG uses a lossy form of compression based on decomposition on the encoded image into 8x8 pixels blocks, and the application of a Discrete Cosine Transform (DCT) to each block of pixels. The DCT operation converts each field of the image from the spatial domain into the frequency domain. JPEG then compress information by quantizing high frequencies coefficients. This loss of information is acceptable, as the human psycho-visual system discards high-frequency information like sharp transitions in intensity. The main drawback of JPEG compression algorithm is the "tiling" effects that appears at high compression ratio.

JPEG2000 intends to overcome several of the shortcomings of JPEG such as better compression ratios, compression scalability, and resolution accuracy. JPEG2000 is an evolution of JPEG, where the main differences are the substitution of the DCT with a wavelet-based method with better scalability characteristic, and the adoption of a more sophisticated entropic coding algorithm. Compared to the previous JPEG standard, JPEG2000 delivers a typical compression gain in the range of 20%, depending on the image characteristics.

III. Related Work

Several dual-domain convolutional neural network-based methods show outstanding performance in reducing image compression artifacts. However, they are unable to handle color images as the compression processes for gray scale and color images are different. Moreover, these methods train a specific model for each compression quality, and they require multiple models to achieve different compression qualities. To address these problems, they [1] proposed an implicit dual-domain convolutional network (IDCN) with a pixel position labeling map and quantization tables as inputs. We proposed an extractor-corrector framework-based dual-domain correction unit (DCU) as the basic component to formulate the IDCN; the implicit dual-domain translation allows the IDCN to handle color images with discrete cosine transform (DCT)-domain priors. A flexible version of IDCN (IDCN-f) was also developed to handle a wide range of compression qualities.

This paper presents a set of full-resolution lossy image compression methods based on neural networks. Each of the architectures they describe can provide variable compression rates during deployment without requiring retraining of the network: each network need only be trained once. All of our architectures consist of a recurrent neural network (RNN)-based encoder and decoder, a binarizer, and a neural network for entropy coding. In this paper [2] they compare RNN types (LSTM, associative LSTM) and introduce a new hybrid of GRU and ResNet. They also study "one-shot" versus additive reconstruction architectures and introduce a new scaled-additive framework. They compare to previous work, showing improvements of 4.3%–8.8% AUC (area under the rate-distortion curve), depending on the perceptual metric used.

The convolutional neural network is widely popular for solving the problems of color image feature extraction. However, in the general network, the interrelationship of the color image channels is neglected. Therefore, a novel quaternion convolutional neural network (QCNN) is proposed in this paper [3], which always treats color triples as a whole to avoid information loss. The original quaternion convolution operation is presented and constructed to fully mix the information of color channels. The quaternion batch normalization and pooling operations are derived and designed in quaternion domain to further ensure the integrity of color information. Meanwhile, the knowledge of the attention mechanism is incorporated to boost the performance of the proposed QCNN. The experiments demonstrate that the proposed model is more efficient than the traditional convolutional neural network and another QCNN with the same structure, and has better performance in color image classification and color image forensics.

In this paper [4] they propose a novel variable-rate learned image compression framework with a conditional autoencoder. Previous learning-based image compression methods mostly require training separate networks for different compression rates so they can yield compressed images of varying quality. In contrast, they train and deploy only one variable-rate image compression network implemented with a conditional autoencoder. They provide two rate control parameters, i.e., the Lagrange multiplier and the quantization bin size, which are given as conditioning variables to the network. Coarse rate adaptation to a target is performed by changing the Lagrange multiplier, while the rate can be further fine-tuned by adjusting the bin size used in quantizing the encoded representation. Their experimental results show that the proposed scheme provides a better rate-distortion trade-off than the traditional variable-rate image compression codes such as JPEG2000 and BPG.

In many biomedical applications, images are stored and transmitted in the form of compressed images. However, typical pattern classifiers are trained using original images. There has been little prior study on how lossily decompressed images would impact the classification performance. In a case study of automatic classification of malaria infected cells [5], they used decompressed cell images as the inputs to deep convolutional neural networks. They evaluated how various lossy image compression methods and varying compression ratios would impact the classification accuracies. Specifically, they compared four compression methods: lossy compression via bi plane reduction, JPEG and JPEG 2000, and sparse autoencoders.

In order to extend the detection of JPEG compressed color images to solve the real-life problem, three-class classification forensics of JPEG compressed color images with the same quantization matrix is proposed. Since the previous methods treat detection of JPEG compressed color images as binary classification and JPEG compression with the same quantization matrix leaves slight tracks, three-class classification forensics of JPEG compressed color images with the same quantization matrix is a new and challenging problem. In this paper [6], two aspects are considered to solve this problem. First, if images are compressed, rounding and truncation error will occur. Thus, preprocessing of images is performed to extract error to highlight statistical difference which can help to classify. Second, the support vector machine (SVM) algorithm is originally designed for the binary classification problem, so dealing with a three-class problem, it is necessary to reconstruct a suitable three-class classifier. Besides, convolutional neural network (CNN) parallelly deal with three channels of the color image.

In this study [8] author have measured the impact of image compression on the classification performance of Convolutional Neural Networks (CNNs). By using a pre-trained CNN to classify compressed images, we have shown that on average, an image can be compressed by a factor 7, 16, 40 for a JPEG, JPEG200 and an HEVC encoder, respectively, while still maintaining a correct classification by the CNN. This study also showed that pre-trained AlexNet CNN was making use of JPEG artifacts learned during the training phase to perform classification. To further study the impact of compression on CNN-based classification, a large set of encoding parameters was explored: color-space, resolution, Quantization Parameter (QP). Main conclusions of this study are that color is essential for classification with AlexNet CNN, and that classification is resilient to image downscaling.

Lossy image compression algorithms are pervasively used to reduce the size of images transmitted over the web and recorded on data storage media. However, they pay for their high compression rate with visual artifacts degrading the user experience. Deep convolutional neural networks have become a widespread tool to address high-level computer vision tasks very successfully. Recently, they have found their way into the areas of low-level computer vision and image processing to solve regression problems mostly with relatively shallow networks. Here [9] author present a novel 12-layer deep convolutional network for image compression artifact suppression with hierarchical skip connections and a multi-scale loss function. They achieve a boost of up to 1.79 dB in PSNR over ordinary JPEG and an improvement of up to 0.36 dB over the best previous ConvNet result.

Multiple description coding (MDC) is able to stably transmit the signal in the un-reliable and non-prioritized networks, which has been broadly studied for several decades. However, the traditional MDC doesn't well leverage image's context features to generate multiple descriptions. In this paper [10] author propose a novel standard-compliant convolutional neural network-based MDC framework in term of image's context features. Firstly, multiple description generator network (MDGN) is designed to produce appearance-similar yet feature-different multiple descriptions automatically according to image's content, which are compressed by standard codec. Secondly, they present multiple description reconstruction network (MDRN) including side reconstruction networks (SRN) and central reconstruction network (CRN). When any one of two lossy descriptions is received at the decoder, SRN network is used to improve the quality of this decoded lossy description by removing the compression artifact and up-sampling simultaneously.

Recent models for learned image compression are based on autoencoders that learn approximately invertible mappings from pixels to a quantized latent representation. The transforms are combined with an entropy model, which is a prior on the latent representation that can be used with standard arithmetic coding algorithms to generate a compressed bitstream. Recently, hierarchical entropy models were introduced as a way to exploit more structure in the latents than previous fully factorized priors, improving compression performance while maintaining end-to-end optimization. Inspired by the success of autoregressive priors in probabilistic generative models, [11] they examine autoregressive, hierarchical, and combined priors as alternatives, weighing their costs and benefits in the context of image compression. While it is well known that autoregressive models can incur a significant computational penalty, they find that in terms of compression performance, autoregressive and hierarchical priors are complementary and can be combined to exploit the probabilistic structure in the latents better than all previous learned models.

IV. Problem Statement

The compression and decompression of the grayscale image are different from that of the color image which relates to the color space conversion. The loss of image information shifts the map of different color space. Thus, the methods of grayscale images are not suitable for color images. Since JPEG is a lossy compression, errors occur during compression and decompression. Compared with JPEG compression with different quantization matrix, JPEG compression with same quantization matrix is more difficult to detect because the quantization matrix in the first compression and subsequent compression are the same, so artifacts caused by different quantization step cannot be utilized. However, truncation error and rounding error occur in the IDCT in JPEG decompression. The information of images which is expressed by pixel value will be stable with an increasing number of compressions (i.e. the loss of the main content and color results in destroying the function of expressing information.). The truncation error and rounding error will reduce with the increasing number of compression, so they are effective for distinguishing JPEG compression. Particularly at high compression rates, the differences between the decompressed and the original image become visible with artifacts that are specific of the applied compression scheme. These are not only unpleasant to see, but also have a negative impact on many low-level vision algorithms [9]. Many compression algorithms rely on tiling the images into blocks, applying a sparsifying transform and re-quantization, followed by a generic loss-less data compression.

V. Conclusion

Image compression is also used in wireless sensors systems to transfer visual information from sensor nodes to central storage and processing sites. In such systems, the transmitting node is often battery-powered and thus heavily power constrained. Transmitting data is often the most expensive part in terms of energy, and strong compression can mitigate this by reducing the required transmit energy at the expense of introducing compression artifacts [3]. Similar challenges are also seen in mobile devices storing data: size and cost constraints limit the amount of memory for data storage, and the energy available on such devices is depleted rapidly. In this paper we review the different image compression techniques with their types, standards and applications.

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