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Supervised by:
Prof. dr. Elena Marchiori

Radboud Universiteit

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JPEG Compression Artifact Removal with Convolutional Neural Networks

Guido C.A. Zuidhof (s4160703)

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Radboud University
Faculty of Science
Institute for Computing and Information Sciences

Toernooiveld 212
6525 EC Nijmegen
The Netherlands
www.ru.nl/icis

Summary

This thesis describes a method for automatic reduction of compression artifacts introduced by JPEG image compression. The aim is to best reconstruct images of any dimension to the state prior to compression.

0.0 (1) Provide an actual summary

Contents

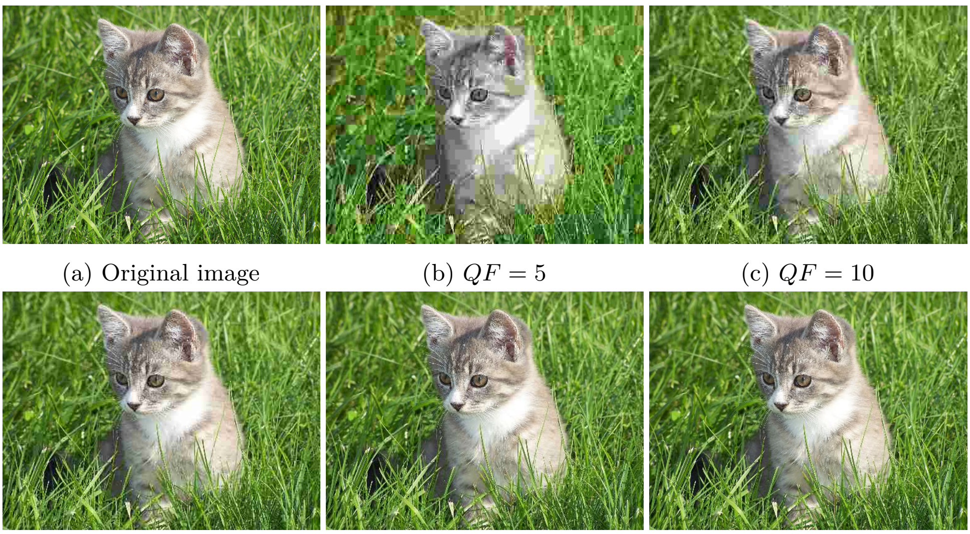
Todo list

CHAPTER 1

Background

1.1 JPEG compression

JPEG is a lossy compression method for digital images. It was named after the *Joint Photographics Experts Group* which authored the standard. This method aims to make the image more compressible by throwing away information which leads to a small difference in perceived quality. In particular it removes high frequency changes in intensity, and often also hue information but not brightness.



(a) Original image (b) $QF = 5$ (c) $QF = 10$

(d) $QF = 20$ (e) $QF = 50$ (f) $QF = 80$

Figure 1.1: Example image after JPEG compression with varying quality factors. Blocking artifacts and hue information loss are especially visible with low quality factor settings.

JPEG compression has one main parameter, the *quality factor (QF)*, which is a value between 0 and 100. A lower quality factor means that more high frequency information is thrown away, which allows for a greater compression ratio, but at the cost of quality loss. In figure 1.2 an image is shown at various quality factor settings.

1.1.1 JPEG compression overview

Different encoding methods exist within the JPEG standard, but the most common is JFIF encoding which consists roughly of the following steps:

(a) Luma (Y) (b) Blue difference (C_b) (c) Red difference (C_r)

Figure 1.2: Color components of our example image in $Y'C_BC_R$ color space.

Transformation to $Y'C_BC_R$ color space The image is converted from RGB color space to the $Y'C_BC_R$ color space. The first component, Y, indicates the brightness. The other two components C_B and C_R represent the *chrominance value* (color). The reason this color space is useful is because the human perceptual system is especially sensitive to changes in brightness, but less so to small differences in color. In later steps this allows for targeted downsampling. Also, there are miscellaneous other small advantages to compressing in this data format.

Downsampling the C_B and C_R components In this step the spatial resolution of the chroma components is reduced by downsampling. This step may be skipped for high quality factor settings.

Splitting into 8×8 blocks Each image channel is split into blocks of 8×8 pixels, starting from the top left. Depending on the chrome subsampling applied in the previous step, the *minimum coded unit (MCU)* block size may be larger than 8×8; most commonly being 16×16 due to a reduction by a factor 2 of the chroma component in both directions. Prior work in JPEG artifact reduction often does not consider the larger blocking effect introduced in the colors of an image, and instead only evaluate on grayscale images.

If necessary, the bottom and right of the images are padded so that the image size is a multiple of the MCU size in both dimensions. Multiple different padding strategies exist in order to prevent artifacts introduced by this padding.

Discrete cosine transform Every 8×8 block is converted to a representation in the frequency domain using a normalized, two-dimensional type-II *discrete cosine transform*(DCT)[9]. This is a method for generating the cosine transform without using the fourier transform. To do this, the image is first zero-centered by subtracting 128 from every pixel (for an 8-bit image). We define a two-dimensional matrix C as:

$$C(k,n) = \frac{1}{\sqrt{N}} \; for\ k,n = 0$$

$$C(k,n) = \sqrt{\frac{2}{N}} \; cos(\pi(2k+1)\frac{n}{2N}) \; otherwise$$

For image U the DCT coefficients matrix G is then given by

$$G = CUC^T.$$

This leads to a matrix of coefficients with high values generally situated in the top left corner (which correspond to the DC coefficient and low frequency AC coefficients). See figure 1.3.

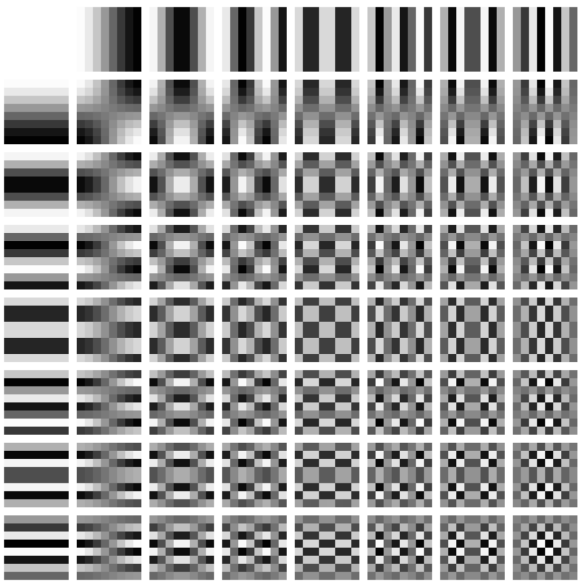


Figure 1.3: *DCT patterns:* the values in the DCT coefficient matrix are weights for each of these patterns (known as *basis functions*) which together construct the original 8×8 image

Quantization Every component in the frequency domain is now divided by a specific value. These values are given by the quantization matrix (which is different for different quality settings of the JPEG compression).

With Q the quantization matrix, the quantized coefficient matrix K is given by:

$$K(k,n) = round(\frac{G(k,n)}{Q(k,n)}) \ for \ k = 0,1,2,...,7; n = 0,1,2,...,7$$

This rounding to the nearest integer is the only lossy part in the encoding, aside from possible downsampling of the C_B and C_R components.

Entropy encoding The values in this matrix are now losslessly compressed. The components are arranged in a “zigzag” order starting in the top left corner, which is favorable for run length encoding due to the zero values at the end.

Decoding Decoding the image simply involves performing the opposite of all previous steps in reverse order. Of course, due to the rounding operation in the quantization step and the possible downsampling of chroma components the decoded image is likely different from the original. This difference may be visible to the human psychoperceptual system in the form of the artifacts described next.

1.2 Artifacts

Due to loss of information, visible artifacts are introduced to the image. Four main types of artifacts are generally observed under JPEG compression of images with a low quality setting.

Ringing artifacts JPEG operates in the frequency domain, representing the image as a sum of oscillating waves. This is not suited for sharp edges, especially with low quality settings, these high frequency waves are rounded to zero. These artifacts are particulary visible in very high contrast images with sharp edges, such as text or simple vector images.

Block coding artifacts Due to the JPEG compression method working on 8×8 blocks, discontinuities at the block boundaries may become visible. With a very low quality setting, only the DC coefficient may be available for every block, leading that block to be a single color. See figure 1.4 for an example image where these artifacts are clearly visible.

Color distortion When the chroma components are subsampled, much of the fine detail is lost. The colors appear more washed out as they correspond to a larger area.

Figure 1.4: *Block coding artifacts:* the 8×8 blocks used internally are clearly visible

Posterization Posterization of an image is the loss of gradual change in tone. Whereas in the original image a color may smoothly go from one color to another, in the compressed image this may be a series of abrupt steps. This can be caused by both chroma component subsampling and quantization of these components.

1.3 Artifact removal

Automated artifact removal methods exist that aim to remove or reduce these artifacts as a post-processing step. These range from hand-crafted algorithms to algorithms with learned parameters. *TODO: Expand on non-DL approaches*

1.3.1 Deep learning

Every year the *ImageNet Large Scale Visual Recognition Challenge (ILSVRC)*[1] [10] is held with as goal to create a system which can automatically determine the content of photographs. In 2010 and 2011 SVM approaches won the classification part of the competition, but ever since 2012 convolutional neural network (CNN) approaches - pioneered in this competition by Krizhevsky, Sutskever and Hinton - have won the competition [6]. These CNN approaches are the state of the art for automated image and speech recognition [4][1]. Machine learning methods which use these connectionist models with many layers (making them *deep*) is often referred to as *deep learning*.

Contrary to regular methods such as SVMs (support vector machines), deep belief networks can automatically learn high level features in a supervised manner [5]. This

[1] http://image-net.org/

is called representation learning. Features learned with automatic methods often outperform hand-crafted feature extractors.

Deep learning methods work by learning and representing features in a hierarchical manner. For image classification for example, in the first layers simple shapes are used as features such as edges or corner. Deeper layers use (possibly non-linear) combinations of the features learned in earlier layers. If for instance a network is trained to recognize faces it may learn features such as eye color and nose shape in one layer, and learn that to best classify a certain person it is the combination of a high activation on the blue eye color, and a lower activation on the other colors.

This representation learning makes it a good candidate for the problem of JPEG compression artifact removal. With the advent of fully convolutional neural networks this can also be applied efficiently to dense prediction tasks like we are dealing with here[7]. Such a network could learn to recognize the artifacts, and reconstruct the image before this artifact was introduced.

1.3.2 Deep learning approaches for artifact removal

TODO: Expand

Dong et al. applied a deep learning model to the problem of artifact removal [3]. They proposed a four layer CNN, AR-CNN, which outperformed existing methods for artifact removal at the time of publication. They note that adding layers comes with great difficulty, as it may not converge. To counter this, they adopt a *easy-to-hard* transfer strategy, where they first train a network to remove artifacts from images compressed with a high quality setting. Then they use the learned weights to initialize a network destined for lower quality setting JPEG images. The same strategy was also used to train deeper networks, where they initialized a five layer network with the weights of an earlier trained four layer network. Svoboda went deeper by adding layers with skip connections making it a residual architecture [13]. This likely makes it easier for the latent clean image to propagate through the network. Technically, however, not a residual function is learned, as opposed to the original ResNet architecture they concatenate the features instead of summing them.

Zhang et al. were able to improve upon these methods considerably [17]. By instead of setting the original image as the training goal, the residual of this image was used as a target. This removes the necessity of a latent image representation in the hidden layers of the network. Also interesting is that this network was not only able to do JPEG artifact removal, but also Gaussian denoising and single image super-resolution.

1.3.3 Sparse coding approaches

TODO

Table 1.1: *LIVE1 dataset validation metrics of prior methods for JPEG artifact removal. To do: Finish this, or leave it out.. Decisions..*

METHOD	PSNR	PSNR-B	SSIM
Quality factor 10			
JPEG	27.77	0.7905	25.33
SA-DCT	28.65	0.8093	28.01
AR-CNN AR-CNN [3]	28.98	0.8217	28.70
L4 Residual [13]	29.08	0.824	28.71
CAS-CNN MS loss [2]	29.36	0.830	28.92
CAS-CNN w/ loss FT [2]	29.44	0.833	29.19
Quality factor 20			
JPEG	30.07	0.8683	27.57
SA-DCT	30.81	0.8781	29.82
AR-CNN [3]	31.29	0.8871	30.76
L4 Residual [13]	31.42	0.890	30.83
L8 Residual [13]	31.51	0.891	30.92
CAS-CNN MS loss [2]	31.67	0.894	30.84
CAS-CNN w/ loss FT [2]	31.70	0.895	30.88

1.4 Evaluative measures

To determine the efficacy of a method for compression artifact removal several quantitative methods are available. Generally it is a distance measure between the restored image and the original image prior to compression.

Mean squared error (MSE) MSE is the simplest measure, often used as the loss function for methods that rely on optimization. It is simply the square of the distance per pixel averaged over all pixels in the dataset. It is given by

$$MSE = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} (x_i - y_i)^2,$$

with N the total amount of pixels, y a predicted pixel, and x the pixel prior to compression.

Peak signal-to-noise ratio (PSNR) Peak signal-to-noise ratio is given by the the ratio of noise to the maximum possible power of the signal, which in this case is the image. It is most often expressed on the logarithmic decibel scale. PSNR in dB is given by

$$PSNR = 10 \cdot log_{10}(\frac{DEPTH^2}{MSE}),$$

with $DEPTH$ the maximum pixel value of the image (255 for 8 bit images).

Structural similarity (SSIM) The Structural Similarity index was developed as an improvement to MSE and PSNR with the goal of being more consistent with how humans perceive images[15]. The index consists of a weighed combination of comparison measures between samples of luminance, constrast and structure across the whole image. These samples are taken with a sliding window approach (generally with an 8×8 window).

Peak signal-to-noise ratio including blocking effects (PSNR-B) PSNR-B is an adaptation of the PSNR introduced by Yim et al. to account for the blocking effect often introduced by image or movie compression algorithms [16]. They introduce the mean squared error including blocking effects $MSE\text{-}B$, which includes a blocking effect factor BEF which is determined from the pixel values on the boundary of the blocks (8×8 in the JPEG case):

$$MSE\text{-}B = MSE + BEF,$$

the PSNR-B then becomes

$$PSNR\text{-}B = 10 \cdot log_{10}(\frac{DEPTH^2}{MSE\text{-}B}).$$

1.5 Datasets

A large amount of different datasets exist for benchmarking and training of image processing, segmentation and classification techniques. For the compression artifact reduction task any image is potentially suitable as ground truth. Ideally, however, the image used as ground truth (prior to JPEG compression) is uncompressed or compressed with a lossless compression algorithm. Below is a list of datasets used in prior work, and other datasets identified as usable in this context. The majority of these datasets are images that have been compressed with a lossy algorithm, albeit it with a high quality factor. *TODO: some accompanying text on each of these.*

LIVE1 dataset [12] 29 grayscale images.

Berkeley Segmentation Dataset (BSD500) [8] Training set of 200 images, validation set of 100 images and a test set of 100 images.

Places365-Standard dataset [18] Training set of 1,803,460 images, validation set of 36,500 images and test set of 328,500 images.

Uncompressed Colour Image Dataset (UCID) [11] 1338 truly uncompressed images taken with the same camera.

1.6 Relevance and impact

To save on bandwidth and storage costs, images are often compressed using a lossy compression algorithm. The compression ratios of these lossy methods is often much better than those of lossless compression algorithms. This compression may result in a noticable degradation in image quality.

This compression often happens unknowningly for the average user. An image attached to a Twitter tweet, uploaded to other social media, or saved in a cloud storage service (such as Dropbox) may be compressed without the user knowing. Also, sometimes digital cameras do not even support the option of storing a lossless version of the original image.

Removing the artifacts introduced by lossy compression can allow for restoring the higher quality original image in these cases.

CHAPTER 2

Methods

TODO: update from proposal, this is currently just a copy paste from the initial proposal version

The aim of this project is to develop a deep learning based approach for reduction of artifacts introduced by JPEG image compression. To achieve this the project has the following objectives:

- Train a system to remove artifacts from compressed images. This mainly involves identifying a suitable convolutional neural network (CNN) architecture, a proper weight initialization, and an efficient training policy. Also, it entails developing a method of dealing with the edges of images.

- Evaluating the performance of the developed system using a large cohort of images, preferably from standardized benchmark datasets which allow for straightforward comparison to prior work.

2.1 Architecture

A challenge in developing convolutional neural networks (and deep neural networks in general) is finding the right architecture. Every year new insights lead to novel architectures which outperform previous year's winning configuration in the ImageNet competition. So far, in this domain, fairly shallow networks have been used. The first obvious way of trying to improve upon prior work is increasing the network depth.

Zhang et al.'s approach of learning the residual instead of the cleaned up image makes sense, however, this may prevent the network from applying higher level "domain" information present in the image, as the original image is not latently available in later layers. Adding a skip connection with the input (JPEG) image to different points at various depths may prove beneficial.

Cavigelli et al. [2] note that learning the residual instead of the cleaned up image does not improve results. So perhaps Zhang's results are not reproducible.

Multiple exit points as presented in [14] may help with the vanishing gradient problem which is especially present in regression networks, by adding a gradient from halfway through the network.Although this only helped marginally for their problem (classification task in the ImageNet competition), it appears that for the CAS-CNN

[2] this was effective, although their method was not tested without these extra exit points.

A fractalnet approach (todo: add citation) may also be an effective way to tackle this problem.

2.2 Miscellaneous improvements

Data augmentation Data augmentation can be beneficial, but it has hardly been applied to this problem. Great care should be taken to only perform pertubations that do not affect the position of the 8x8 blocks. Hue, value and saturation jittering should be fine. Augmentations like flipping can only be applied if the image is a multiple of 8 in the specific dimension.

Alternative training sets The previous, related work mentioned in the background chapter is generally trained on either a subset of the evaluation datasets, or images from the ImageNet competition. These images are already compressed, and may not be a suitable starting point. Alternative training sets could be sought after which are losslessly compressed, or compressed with high quality settings.

2.3 Datasets

Standardized datasets exist for evaluating the performance of image processing tasks such as artifact removal. TODO expand: `https://drive.google.com/folderview?id=0B-_yeZDtQSnobXIzeHV5SjY5NzA&usp=sharing` Berkeley Segmentation Dataset (BSD) `https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/resources.html#bsds500`

CHAPTER 3

Schedule

TODO: Obviously this won't be in the final version :-) This chapter describes a rough planning for the full thesis project. It is hard to foresee the time required for the individual goals of the project which makes it likely that time lines will shift.

December-January	Proposal, background study Kicking off the project, writing the project proposal. Final version by January.
January	Framework, explorative experiments, write background Create environment for testing and running experiments. Finish background chapter for thesis, detailing the inner working of JPEG, overview of artifacts, and existing (non-deep learning) approaches for artifact removal (5 to 7 pages?).
February	Gather datasets, implement architectures Collect datasets to evaluate the project's system. If feeling ambitious, also generate random vector images. Apply the network architectures described in section 2.1, as well as tweaking their hyperparameters. Aside from tweaking the parameters, different pre and postprocessing methods such as data augmentation will be explored to further increase the performance of the networks. Finish methods chapter of thesis (5 pages?).
March-March	Further tweaking, evaluate different initialization and sampling strategies Proper initialization is very important for this problem. Evaluate some different initialization strategies as described in literature, and continue tweaking architectures. Collect first results and describe these. Create shell for results chapter (around 3 pages?)
Early April	Run final experiments, gather and describe results.
April	Buffer and finalizing the thesis Buffer for previous steps, room for stretch goals, writing the final version of the thesis. Late April or start of May: thesis presentation and defense, concluding the project.

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