Eidgenössische Technische Hochschule Zürich
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Efficient Task Aware Super-Resolution and Colorization

For Image and Video Domain

Semester Project

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Abstract

The abstract gives a concise overview of the work you have done. The reader shall be able to decide whether the work which has been done is interesting for him by reading the abstract. Provide a brief account on the following questions:

- What is the problem you worked on? (Introduction)
- How did you tackle the problem? (Materials and Methods)
- What were your results and findings? (Results)
- Why are your findings significant? (Conclusion)

The abstract should approximately cover half of a page, and does generally not contain citations.

Abbreviations

COL colored image

GRY grayscale image

HR high-resolution image

IC Image-Colorization

LR low-resolution image

SHR task-aware-high-resolution image

SISR Single-Image-Super-Resolution

SLR task-aware-low-resolution image

SR Super-Resolution

TAD Task-Aware-Downscaling

VSR Video Super-Resolution

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1 Introduction

With the rise of deep learning in image processing Super-Resolution (SR) and Image-Colorization (IC) in both the image and the video domain have received significant attention [20]. While SR aims to reconstruct a high-resolution image (HR) from a low-resolution image (LR), image colorization deals with the transformation from an uncolored, grayscale image (GRY) to a RGB colored image (COL). However, in most of the recent works (e.g. [19], [18], [8], [17]) the problem of downscaling and upscaling or decolorization and colorization are regarded as seperate problems although upscaling often is preceded by downscaling, leading to a loss of information from the downscaling process which makes the inverse problem of SR highly ill-posed [9]. Despite of the large progress in SR in the last years ([20]) very specific details therefore often cannot be reconstructed, when interpolation is used for downsampling. However, as shown in Fig. 1 the downsampling method has a large impact on the performance of the subsequent upscaling task.

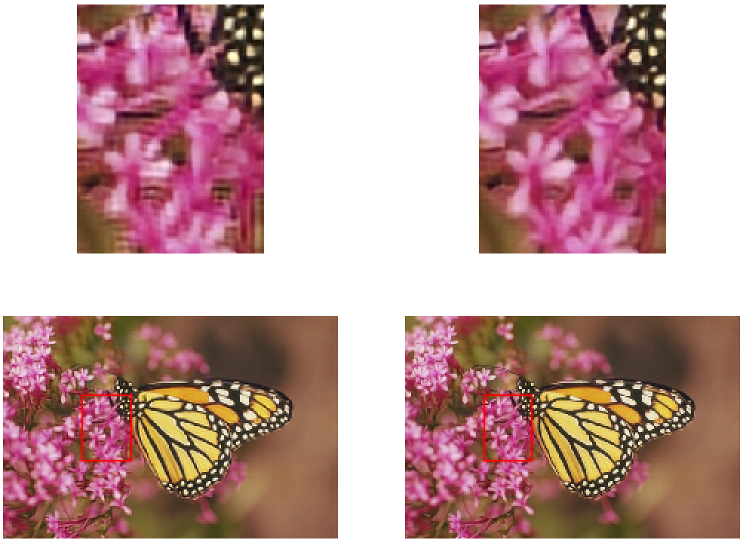

Figure 1: Comparison between an upscaled image based on bicubic downsampled (left) and task-aware downsampled (right) LR image applied on the same model with upscaling factor 4.

As can be seen above a task-aware approach can dramatically improve the performance of existing super-resolution models. However, the research on task-aware downscaling methods is a very new field and therefore there still are a lot of unresolved issues such as the effect of perturbation or the feasibility of applying it to tasks other than SISR and IC.

1.1 Focus of this Work

For this reason this work focuses on TAD for several standard computer vision problems such as super-resolution or colorization in both the image and video domain, as recently purposed by Heewon Kim et. alt. ([9]) for the image domain only. However, as shown in Fig. 2 the TAD implementation purposed in [9] suffers from vulnerability against perturbation of the downscaled image. Although the purposed model is quite shallow having 10 convolutions for each scaling process only, there still is potential for improvement, which especially gains importance when TAD is applied to the video domain (for real-time capabilites).

Figure 2: Problems of task aware downscaling as purposed by [9]: Perturbation (left), Runtime (right)

Therefore the goals of this work are the following:

- reimplement and evaluate the TAD framework purposed in ([9])
- improve the TAD framework especially with regards on the trade-off between model-complexity (runtime) and restoring quality (PSNR) as well as with regards on robustness against perturbations
- extend the TAD framework to the video domain

By that to the best of our knowledge this work is the first one using deep learning for downscaling in the video domain.

1.2 Thesis Organization

After the problem statement Chapter 1 related works are introduced for both the image and video domain Chapter 2. Chapter 3 explains the methods that are used in order to achieve the goals described above and which are evaluated in Chapter 4. A final discussion of the results as well as an outlook on further work can be found in Chapter 5. Further visualization and experiments are shown in the abstract.

2 Related Work

In the following previous work in super-resolution, colorization and task-aware-downscaling are presented. At the end of each section the models used for comparison and evaluation of the the underlying approach are further explained in detail. Thereby the models were selected based on several criterias performance compared to the state-of-the-art, the use as benchmark in related papers and availability of (pretrained) models.

2.1 Super-Resolution in Image Domain

The problem of SR in the image domain is called SISR and is shown in Fig. 3. A lot of approaches have been tried in order to cope with the SISR problem. While early approaches such as bicubic and Lanczos [5] tackle the problem using simple deterministic filters which are computational cheap but produce blurry results and lack in high frequency details, more recent approaches approach the problem using example-based methods such as sparse encoding or deep learning methods.

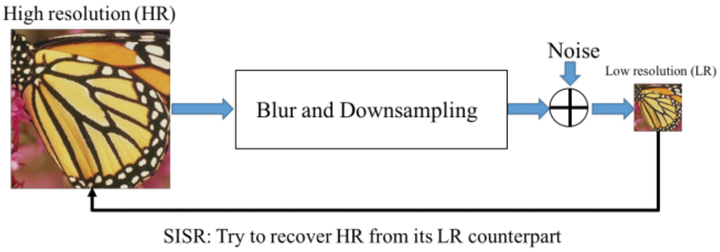

Figure 3: General SISR problem according to [22].

Sparsity-based techniques assumes the LR image to be transformable in another domain (usually a dictionary of image atoms [6]) and tries to find correspondences between the LR and HR patches in the transformed space, as implemented in [4]. However, these techniques usually are very computationally expensive. Among other learning based approaches such as the use of random forests [14], in-place example regression models [21] or adjusted anchored neighborhood regression [16], in terms of accuracy applying CNN based approaches have shown the largest success. [1] Dong et al. [2] trained a shallow CNN end-to-end to build the HR image based on a bicubicly upscaled LR image. This approach was improved by Kim et al. [10] (VDSR) using a deeper network (20 layers) and cascading small filters many times in a deep network structure to exploit contextual

[1] An overview of various other deep learning based approaches for SISR can be found in [22].

information over large image regions in an efficient way. By advancing the network model VDSR was further improved by Lim et al. [11] which got the best results in the NTIRE2017 Super-Resolution Challenge [1].

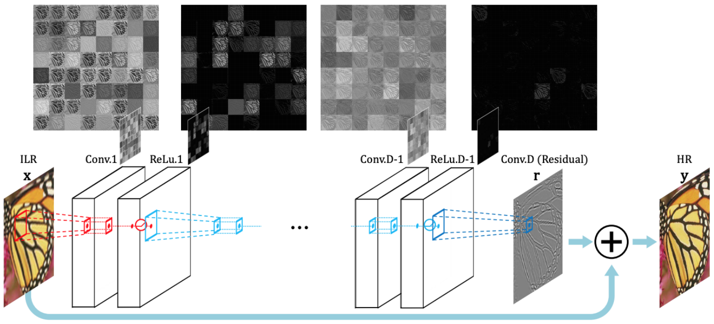

Figure 4: Overview of VDSR network design [10].

2.2 Super-Resolution in Video Domain

Video Super-Resolution (VSR) combines information from multiple adjacent LR frames to take temporal information into account, leading to higher quality results. Takeda et al. [15] apply a 3D kernel regression on a patch of adjacent LR frames to implicitly encounter temporal information. Since purposed by Caballero et al. [3] end-to-end approaches including motion compensation such as the CNN framework from [3] have large success in the VSR area. Liu et al. [12] added temporal addaptivity to the framework to be able to aggregate the resulting HR frame based on a weighted sum of several estimates as well as a varying number of input LR frames. Sajjadi et al. [13] purposed a frame-recurrent architecture iteratively using the previously inferred HR frames for the subsequent prediction. Wang et al. [17] (SOFVSR) implemented an end-to-end trainable approach to predict both, the HR frame as well as the HR optical flow. Therefore, first the HR optical flow is inferred in a coarse-to-fine manner, then motion compensation is performed according to the HR optical flows and finally, the compensated LR inputs are fed to a super-resolution network to generate the HR frame estimate (comp. Fig. 5).

2.3 Colorization

Image colorization methods can be categorized in two categories: Non-parametric approaches, such as [7], model the correspondence between the grayscale and the

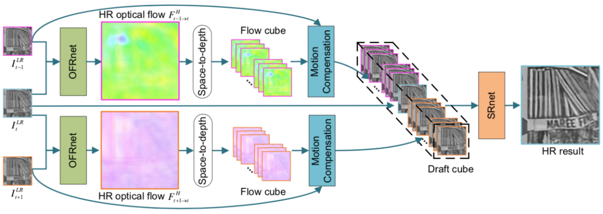

Figure 5: Overview of SOFVSR pipeline [17].

colored image by finding analogeous regions in reference image(s), while parameteric models learns this correspondence from large datasets, transforming the colorization problem into a regression problem. Zhang et al. [23] (CIC) purpose posing colorization as a classification task and use class-rebalancing at training time to increase the diversity of colors in the result, using the CNN shown in Fig. 6 and not requiring any user-interaction.

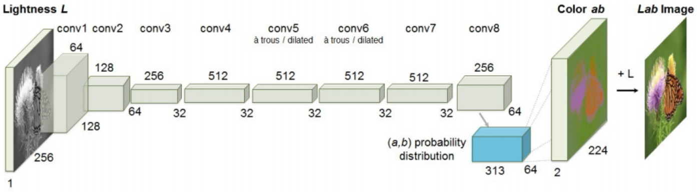

Figure 6: Overview of CIC network design [23].

2.4 Task-Aware-Downscaling

Over all of the problems stated above most of the approaches merely take into account one side of the process, e.g. by fixing the transformation HR to LR to bicubic interpolation in order to large amount of training data and focusing on estimating the inverse transformation. Kim et al. [9] (TAID) purpose taking into account the downscaling method in order to improve the upscaling performance, by training an autoencoder in an end-to-end manner while the latent space representation again is an image of same size as the LR image. The loss function thereby contains both the difference between the decoded SHR and the original HR image as well as the difference between the encoded SLR and the bicubic interpolated LR image, such that the SLR image is a humanly understandable representation. Next to SISR the approach is shown to be applicable for large scale factor up to 128 as well as for colorization.

3 Approach

In the following the methods developed within the underlying project are presented. After introducing into the general design of TAD in Section 3.1 the implementation for each task are shown, i.e. for SISR in Section 3.2, for VSR in Section 3.3 and for IC in Section 3.4.

3.1 General Design

The general idea behind TAD is that a high-dimensional input (e.g. a high-resoluted or colored image) is transformed in a low-dimensional space so that it first can be inverse transfored as good as possible and second still is human-understandable in lower dimensional space. Besides, both transformations should be computationally efficient.

Autoencoder Network Design

In order to fulfill the requirements above an reasonably shallow autoencoder is used, consisting of a combination between convolutional and subpixel convolutional (pixel-shuffle and inverse pixel-shuffle) layers, as shown in Fig. 7 using the example of SISR.
In the first part, g_ϕ, a high-dimensional input (left: HR) is first filtered using two convolutional layers, then downscaled using inverse subpixel convolutions. Afterwards several *Resblocks* perform further transformations, followed by two convolutional layers. As discussed below the encoding is added to a trivially interpolated low-dimensional representation (lower middle: LR) forming the autoencoder's task-aware-low-resolution image (SLR) (upper middle). The inverse transformation, f_θ, has a similar inversed structure and results in the task-aware-high-resolution image (SHR) (right).

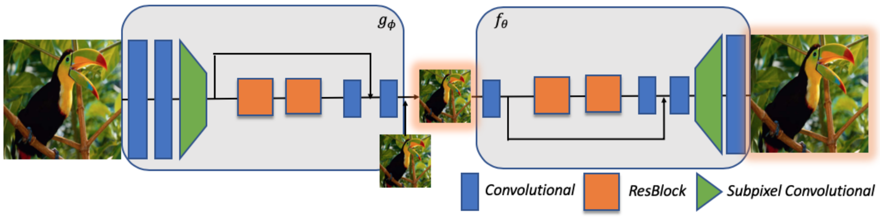

Figure 7: Overview of TAD autoencoder network design for SISR task.

Thereby, a *Resblock* is a convolutional-recurrent sequence as follows:

$$Resblock(x) = x + Conv2D(ReLU(Conv2D(x)))$$

The *Resblocks* are important to conserve information throughout the layers, as demonstrated in Chapter 4 the number of *Resblock* has a large impact on both the performance and runtime of the model.
Since this network design does not continuously downscales the input but applies inverse pixel shuffeling to downscale while all other layers of the downscaling network g_ϕ do not alter their inputs shape (and vice versa for the upscaling network f_θ), the networks can be easily modified.
The overall network structure is similiar (although not identical) to the network purposed in [9].

Loss Function

The loss function L consists of two parts: The first one, L_{TASK}, is task-dependent and states the difference between the decoders output X_{SHR} and the desired output X_{GT}, e.g. the original HR in the SISR task.

$$L_{TASK} = L1(X_{GT}, X_{SHR})$$

The second part, L_{LATENT}, encodes the human-readibility of the low-dimensional representation. To do so it is assumed that the optimal latent space encoding is not equal but similar to trivial lower dimensional representation like a (bilinear) interpolated LR. Next to simplifying the loss function this assumptions has the benefit of ensuring (faster) convergence, since merely a difference between the interpolated representation and the more optimal encoding has the be derived in the learning process. Also the down- and upscaling can be learnt more *independently* since the lower dimensional representation is always guaranteed to be *useful* for upscaling. So L_{LATENT} is the distance between the interpolated guidance image X_{GD} and the actual encoding X_{SLR}:

$$L_{LATENT} = \begin{cases} L1(X_{GD}, X_{SLR}) & \text{if } ||L1/d_{max}|| \geq \epsilon \\ 0.0 & \text{otherwise} \end{cases}$$

with $||L1/d_{max}||$ being the $L1(X_{GD}, X_{SLR})$ loss normalized by the maximal deviation between X_{GD} and X_{SLR}. Hence, L_{LATENT} is zero in an $l1$-ball around the guidance image, ensuring that SLR is close to the guidance image but also helps to prevent overfitting to the trivial solution $X_{GD} = X_{SLR} \Leftrightarrow g_\phi = 0$.
The overall loss function is a weighted sum of both of the loss function introduced above. The relative weight (α, β) is of large importance for the trade-off between the readibility requirement and the performance of the model's upscaling part (super resolution, colorization). However, since the readibility requirement typically

is *weaker* (i.e. *easier* to fulfill since the network is guided by a well-readable low-dimensional image) typically $\alpha >> \beta$.

$$L = \alpha L_{TASK} + \beta L_{LATENT}$$

3.2 Task-Aware Image Downscaling

3.3 Task-Aware Video Downscaling

3.4 Task-Aware Image Colorization

4 Experiments and Results

- PSNR for different scales
- Noise vs performance
- different lambdas
- time vs network size
- approaches of video scaling, i.e. flow, direct external
- noise resistence normal downscaling vs tar downscaling
- large scales (training directly, performance of other non-trained scales)
- scale and colorization for x4
- super large scale for videos
- torch - implementation of inverse pixel shuffeling

5 Discussion and Conclusion

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A Appendix

In the appendix, list the following material:

- Data (evaluation tables, graphs etc.)
- Program code
- Further material