Go Deep into Super-Resolution: A Systematic Review Based on Problem Decomposition and Classification

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Abstract. Super-resolution (SR) has been attracting research attention in recent decades because of the growing demand for higher resolution. A large variety of algorithms in the computer vision field was applied to improve this issue. In this paper, we provide a problem-based analysis for the SR problem by dissembling the original issue into several subproblems. We broadly bring these problems under three main levels, information augmentation, mapping, and orientation and control. Furthermore, we elaborate on various research perspectives under each level, summarizing typical and advanced algorithms improved on related processes. Besides, we discuss the similar ideas and evolutionary relationships revealed in different methods. We also arrange some popular datasets and competitions in the SR field. By doing this, we aim to inspire deeper investigation and enlighten possible research sites of SR problems in the future.

Keywords: Super-resolution, Motion estimation, Interpolation, Deep learning, Regularization

1 Introduction

Super-resolution (SR) is an important branch of computer vision and image processing, referring to high-resolution reconstruction. Traditional reconstruction methods improve definition using structural or statistical information. In recent years, the concept of deep learning has been introduced into SR problems. Many efficient deep networks such as linear network, residual network (ResNet), densely connected network (DenseNet), generative adversarial network (GAN), attention-based network, etc. have been verified valid for extracting underlying correlated information and reconstructing high-resolution images.

Super-resolution has a broad application prospect. Image super-resolution (ISR) can be applied in a broad field such as medical science [1], surveillance [2], and astronomy to improve the quality of images, while video super-resolution (VSR) has great application potential in improving video definition as well as promoting video compression and transmission.

So far, there are some existing SR overviews. Many earlier works were conducted on traditional algorithms [3-5]. After that, Wang et al. [6] and Anwar et al. [7] provided reviews on deep learning based ISR techniques respectively in 2019. Besides, Liu et al

[8]. did a systematic survey on VSR tasks. Most of these works concentrate on horizontal classification, emphasizing the divergence between network structure and specific skills in methods. Although both traditional and deep learning methods are frequently mentioned, they are generally discussed separately and exclusively, so do VSR and ISR. In this paper, unlike the previous surveys, we analyze SR algorithms in a vertical and correlative way, arranging typical and advanced methods systematically in view of the concrete problems they are designed to solve. By doing this comprehensive research, we provide inspiration for possible research sites to super-resolution problems in the future.

The rest of the paper is structured as follows. Section two gives a problem definition and discusses differences as well as the relationship between SR and other similar problems. In section three, we divide the SR problem into three levels and construct a large granularity of classification of each level. Section four briefly introduces the dataset and competition of the SR technique. Finally, in section five, we discuss the promising research directions of SR.

2 Problem Definition

Super-resolution is a compounded issue that refers to recovering a high-resolution (HR) image (or sequence) from a low-resolution (LR) image (or sequence). It involves a class of fundamental techniques in the field of computer vision and image processing, including image registration, feature extraction, deep learning, optimization algorithms, image quality assessment, etc. [9]

SR is related to two familiar problems, denoising and image self-interpolation. Denoising is a similar restoration process of the degraded high-quality image. The core of which is to remove the abundant information from the original image, that is, approximate the noise distribution or design a filter to sift nondestructive image from additional noise, but it does not change the number of pixels in the image. Denoising can be considered as a subprocess of SR, for the pixel increase process usually brings about unexpected noise at the same time. As for image self-interpolation, which is also known as up-sampling, it aims to magnify the image for better perceptual acceptability. However, single image interpolation cannot recover the high-frequency components lost or degraded during the LR sampling process [10]. For this reason, image self-interpolation defers from the SR problem but is used as another subprocess integrated with deep learning methods to adjust image size [11-14].

In its appearance, super-resolution derives Image super-resolution (ISR) and video super-resolution (VSR) according to task sources. ISR focuses on independent image reconstruction, and VSR stems from ISR and aims at restoring HR videos from multiple LR frames [8]. Seeing from the process, ISR and VSR are generally unanimous yet put emphasis on different aspects. ISR usually takes advantage of pre-learned information to establish a uniform mapping between LR image and HR image. Comparatively, VSR pays more attention to temporal information and correlation among frames, thus emphasizing motion estimation for an effective solution. But in general, they share plenty of common ideas in increasing resolution.

From the perspective of problem decomposition, the SR problem mainly involves three key issues. Since HR image carries more pixels and details than LR image, the first issue is how to increase the effective information contained in LR resource. Additionally, if we are provided with large amounts of reference LR-HR pairs for training, the second issue is how can we extract a universal mapping relationship between them. Finally, the last issue lies in the algorithms themselves, according to how to achieve a high processing speed and apply to various tasks. We will discuss solutions to these issues in the following section.

3 Solution to Super-Resolution problem

A variety of SR algorithms and models have been proposed during the past decades. From the angle of the key issues, we divide these methods into three levels, considering little about implementation details but focusing on the concrete problem they respectively solved. The first level is information augmentation, commonly referring to aliasing compensation to add additional information in the subpixel. The second level is establishing mappings, which could come in many forms. And the last level mainly involves the optimization and control skills of the mapping algorithm. Many of the existing approaches, especially traditional methods, reveal good performance by providing resolution to one of the three subproblems, while a vast of nowadays deep learning networks solve two or more levels at the same time using a combination of different convolution blocks. Fig. 1 shows a classification of popular methodologies proposed from corresponding perspectives. In this section, we elaborate on the three levels of SR resolution from the methodological point of view, citing typical works and providing details of this classification.

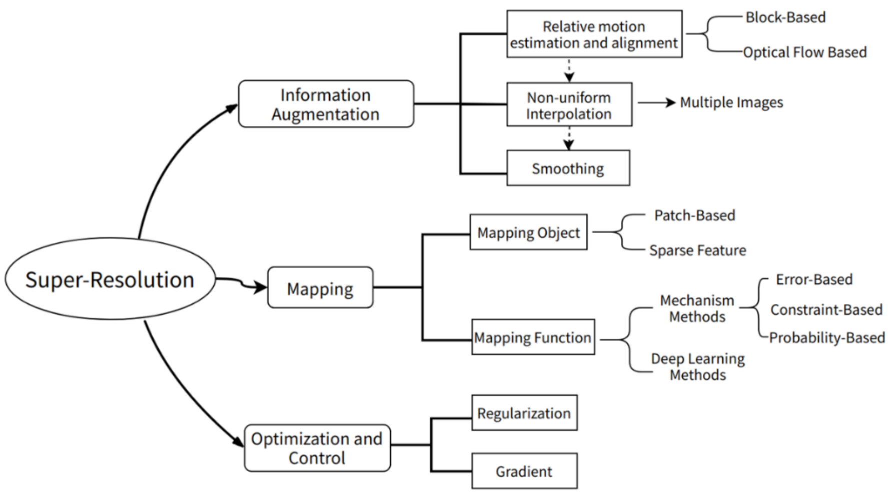

Fig. 1. Classification of SR partial solution

3.1 Information Augmentation

Transferring low resolution to high resolution involves an important procedure to add additional pixels. The interpolation of a single image is usually considered as a procedure of up-sampling and magnification, while the basic premise for increasing the spatial resolution in SR techniques is the availability of multiple LR images captured from the same scene [10]. They can be either statistic images captured from slightly different angles or a series of continuous frames (video). If the LR images contain aliasing and shift in subpixel precision, we can exploit new information contained in each image and interpolate them to an HR image.

Obtaining HR images by interpolation generally consists of three stages, 1) relative motion estimation and alignment, 2) non-uniform interpolation, and 3) image smoothing. Many works were conducted on one or more stages, contributing to better interpolation results.

For the first stage, motion estimation and alignment are special techniques commonly used in video coding to compress video signals [15-17], and the purpose of them to SR problem is to locate and correct the pixel offset of multi-frame images, thus introducing subpixel information for subsequent operations. Two classical and fundamental directions are block-based motion estimation (BBME) and optical flow-based motion estimation. Baraskar et al. surveyed block-based search, dividing traditional methods into non-rectangular search, rectangular search, and multi-pattern search [18]. In recent years, various strategies such as deformable convolution [19], hierarchical hybrid [20], and new optimizer [21] were also applied on BBME. Optical flow-based researches mainly stemmed from Horn-Schunck(HS) [22] and Lucas-Kanade(LK) [23] approaches. Besides top-performing handcrafted algorithms such as DeepFlow [24] and EpicFlow [25], deep-learning networks were also widely applied to this field. FlowNet series [26, 27] and SpyNet [28] were typical applications of deep-learning in optical flow method, and many state-of-the-art methods were developed on their basis [29-32]. It is worth mentioning that some methods combined alignment and interpolation into one step [33], and others may exploit the spatial or spatial-temporal information for feature extraction without aligning neighboring frames [34-37].

For the second stage, compared with image self-interpolation, non-uniform interpolation refers to multiple LR interpolating into one HR, that is, interpolation with increased information, yet some up-sampling methods like Bicubic (BI), Lanczos, and discrete wavelet transform (DWT) can be also adopted to multiple images. Furthermore, Panagiotopoulou et al. proposed Kriging interpolation [38], Sanchez-Beato et al. applied B-spline filter after Delaunay Triangulation interpolation [39], and Vandewalle et al. proposed a non-uniform interpolation using frequency domain registration [40]. There are also some convolution-based interpolation methods combined with deep learning networks such as bidirectional predictive network (BiPN) [41], PhaseNet [42], Deep Voxel Flow [43], and Adaptive Convolution [44].

After the above two stages, a lot of noise and blur are added during the information increase process. It is necessary to smooth or enhance the image to raise perceptional acceptability. Notably, the smoothing operation can be placed in any steps of SR and is not necessarily constrained to the information augmentation level.

3.2 Mapping

In the case of having reference LR-HR images for training in advance, establishing a uniform mapping function from LR to HR is a more direct and effective method. Its underlying target is to learn or approximate a mapping relationship between source and target, and this relationship is usually non-linear and non-unique. Generally, the mapping operation is an integrated process, some other techniques such as interpolation and optimization are also used as pre-processing or post-processing along with mapping.

Among previous researches, the innovation of mapping establishment mainly fell into two aspects: how to establish mappings according to the mapping objects, and how to define accurate mapping functions based on mapping itself.

Seeing from the angle of mapping object, mapping from image to image directly has unexpected penalties of complexity and overfitting. Therefore, researchers came up with some effective ideas such as cropping images to hierarchical scales or establishing mapping in other domains [45]. A common idea was patch-based mapping [46-50]. Like BBME, researchers considered splitting the images into patches and obtaining smaller mapping units. By doing this, the computation and parameters will be reduced, and patches in many locations have some similarities, which can greatly increase the training dataset. In addition, another research idea was extracting sparse mapping features [51, 52], which contributed to reducing the impact of noise while increasing generality.

On the other hand, researchers also considered methods to approximate a better and more accurate mapping relationship. This relationship can be expressed by several constraint equations or model parameters in networks or else. Traditional mechanism approaches are mainly divided into three categories. The first is the error-based method, represented by Iterative Back Projection (IBP) from Iran and Peleg [53]. The second is the constraint-based method, a typical example of which is Projection onto convex sets (POCS) [54]. Furthermore, the last category is the probability-based method, which generally stems from the Maximum a posterior (MAP) algorithm frame. For deep learning based approaches, many were inspired by mechanism ideas. Deep back-projection networks (DBPN) [55] proposed by Haris et al. is representative of deep network applied on IBP method.

3.3 Optimization and Control

Compared with the former two levels about information augmentation and mapping, the optimization and control of the algorithm usually do not appear as an independent step but are of equal importance with the above two. There are two main objectives of this level. One is to make key areas that directly affect perceptual acceptability clearer, the other is to reduce the complexity and narrow solution space. The common solution to these objectives comes down to various forms of prior information provided for computation control.

Many algorithms achieved good performance by giving pertinent orientation to the existing approach. One of the dominant forms is regularization, of which the essence is to provide a prior rule to restrict the algorithm. The prior probability term of HR in the

MAP method is an epitome of the regular term, which is based on statistical features of HR images, playing a key role in optimizing the resulting quality. Many subsequent methods under the MAP framework improved by modifying the regular term [56-58]. Also, most methods in deep learning add regular terms to the loss function to limit the complexity and increase the generalization of the model. In addition, there are some methods extracting edges or gradients as prior information to generate better high-frequency details, such as SRCNN-PR [59], utilizing gradient information, and DEGREE [60], a depth residual network with prior edge information.

4 Datasets and Competitions

Many open datasets are available in SR training and testing, including image sets and video sets. In Table 1, we list some commonly used benchmark datasets and provide brief information about them. These datasets vary in amount, resolution, and contained category, supporting different training tasks and requirements.

Table 1. Open Datasets in SR

Type	Dataset	Amount	Resolution	Other information
Image datasets	Set14	14	492*446	A small image set widely used for test
	Manga109	109	826*1169	Images from manga volumes
	BSDS500	500	432*370	BSDS provide various datasets with different amount
	Urban100	100	984*797	Images of human-made structures
	OST	10624	553*440	A large image set of outdoor scenes
	DIV2K	1000	1972*1437	2K resolution image set
Video datasets	YUV25	25	386*288	Videos in YUV color space
	Vid4	4	720*500	4 videos contain high-frequency details
	CDVL	100	1920*1080	2K resolution video set
	UVGD	7	3840*2160	4K resolution video set
	Vimeo-90K	91701	448*256	One of the largest VSR dataset
	REDS	270	1280*720	Videos with large movement between frames

Additionally, plenty of international SR competitions have been organized by companies and conferences in recent years, contributing to the development of new methods as well as the improvement of existing methods in super-resolution. One of the authoritative competitions in image and video enhancement field is New Trends in Image Restoration and Enhancement (NTIRE) competition. In NTIRE 2021, team NTU-Slab won the championship with BasicVSR++ on the VSR track [61]. This method reached state of the art and achieved an unprecedented 29.04dB on the Vid4 dataset. Besides, Perceptual Image Restoration and Manipulation (PIRM) and Advances in Image Manipulation (AIM) are another two famous events, many competitive approaches such as ESRGAN [62], EVESRNet and GP-NAS are coming from them.

5 Conclusion

In this paper, we provide an in-depth analysis of super-resolution, decomposing the original problem into several interrelated subproblems. We also enumerate and classify the existing classical and effective methods from a solution-based perspective. Additionally, it should be emphasized that many algorithms cannot broadly fit into a single subproblem. Take deep learning based approach as an example, although the core of deep learning is to establish a set of universal mapping rules by training inner parameters, other steps such as motion estimation, interpolation, feature selection, smoothing, and optimization may also be integrated into the network. In view of space, we did not elaborate on the specific implementing process of various algorithms, and the selected works are relatively limited. However. the mechanism decomposition of SR has great significance for enlightening future research directions. We desire to inspire novel solutions to a certain subproblem that may bring about a great improvement when combined with other existing approaches, for instance, an intended modification of network module, or applying skills introduced from another research field.

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