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A SYSTEM FOR SUPER RESOLUTION USING DEEP LEARNING

Technical field of invention:

[001] Present invention in general relates to artificial intelligence, and more specifically to super resolution using deep learning which provides an end-to-end mapping between low and high-resolution images.

Background of the invention:

[002] The background information herein below relates to the present disclosure but is not necessarily prior art.

[003] The highly challenging task of estimating a high resolution (HR) image from its low-resolution(LR) counterpart is referred to as super-resolution (SR). SR received substantial attention from within the computer vision research community and has a wide range of applications s in many areas such as HDTV, medical imaging, satellite imaging, face recognition and surveillance etc.

[004] The optimization target of supervised SR algorithms is commonly the minimization of the mean squared error (MSE) between the recovered HR image and the ground truth. This is convenient as minimizing MSE also maximizes the peak signal-to-noise ratio (PSNR), which is a common measure used to evaluate and compare SR algorithms. However, the ability of MSE (and PSNR) to capture perceptually relevant differences, such as high texture detail, is very limited as they are defined based on pixel-wise image differences.

[005] In proposed invention a super-resolution generative adversarial network (SRGAN) forwhich employ a deep residual network (ResNet) with skip-connection and diverge from MSE as the sole optimization target. Different from previous works, we define a novel perceptual loss using high-level feature maps of the VGG network combined with a discriminator that encourages solutions perceptually hard to distinguish from the HR reference images.

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[006] Although various attempts are made before, for providingsuper resolution using deep learning and few of them are such as-CN107154021A discloses image super resolution method based on deep layer thresholding convolutional neural networks, CN107240066A discloses image super resolution rebuilding algorithm based on shallow- layer and deep layer convolutional neural networks, 20180075581 discloses super resolution using a generative adversarial network

[007] There exist many drawbacks in the existing system.So,there is a need to developsuper resolution using deep learning.

Objective of the invention

[008] An objective of the present invention is to attempt to overcome the problems of the prior art and provide super resolution using deep learning.

[009] In a preferred embodiment, the present invention testing different algorithms and finding out the one that directly learns an end-to-end mapping between low and high-resolution images

[0010] It is therefore an object of the invention is comparative study of the results obtained from all the four networks and analyze.

[0011] It is therefore an object of the invention is testing and analyzing the model on different images obtained from CCTVcameras to validate the proposed application.

[0012] These and other objects and characteristics of the present invention will become apparent from the further disclosure to be made in the detailed description given below.

Summary of the invention

[0013] Accordingly following invention providessuper resolution using deep learning.The proposeinvention provides an end-to-end mapping between low and high-resolution images

[0014] The invention direct implementation and comparison of the papers with some tweaks to the network and loss functions and compared four networks with three are CNN based networks namely SRCNN, DCSCN, WDSR and fourth one is GAN based SRGAN.

[0015] At present, there are many algorithms for super-resolution (SR). In the research ofInterpolation-based image super-resolution reconstruction algorithms, the input LR image is mainly denoised, deblurred, and up-sampled to improve the image resolution. Among them, the more classic interpolation algorithms include: the nearest neighbor interpolation, the linear interpolation, the bicubic interpolation, and the spline interpolation. The most classic dictionary-based SR algorithm is sparse encoding, which seeks a sparse representation of LR input image blocks and then uses the coefficients of this sparse representation to generate HR output.

[0016] In order that the manner in which the above-cited and other advantages and objects of the invention are obtained, a more particular description of the invention briefly described above will be referred, which are illustrated in the appended drawing. Understanding that these drawing depict only typical embodiment of the invention and therefore not to be considered limiting on its scope, the invention will be described with additional specificity and details through the use of the accompanying drawing.

Detailed description of the invention:

[0017] The present invention relates tosuper resolution using deep learning More particularly proposed invention providesan end-to-end mapping between low and high-resolution images

[0018] SRCNN consider a single low-resolution image, we first upscale it to the desired sizeusing bicubic interpolation, which is the only preprocessing we perform. Let us denote the interpolated image as Y. Our goal is to recover from Y an image F(Y) thatis as similar as possible to the ground truth high-resolution image X. For the ease ofpresentation, we still call Y a “low-resolution” image, although it has the same size asX. We wish to learn a mapping F, which conceptually consists of three operations

[0019] Patch extraction and representation: this operation extracts (overlapping) patchesfrom the low-resolution image Y and represents each patch as a high-dimensionalvector. These

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vectors comprise a set of feature maps, of which the number equals tothe dimensionality of the vectors.

[0020] DCSCNstart with only 1 CNN layer with small dataset and then grow the numberof layers, filters and the data. When it stopped improving performance, we tried to change the model structure and tried lots of deep learning technics like mini-batch, dropout, batch normalization, regularizations, initializations, optimizers and activators to learn the meanings of using each structures and technics. Finally, we carefully chose structures and hyper parameters which will suit for SISR task and build our final model.

[0021] WDSR two-layer residual blocks are specifically studied following baseline EDSR.Assume the width of identity mapping pathway is w1 and width before activation inside residual block is w2. We introduce expansion factor before activation as r thusw2 = r × w1. In the vanilla residual networks (e.g., used in EDSR and MDSR) wehave w2 = w1 and the number of parameters are 2 × w 2 1 × k 2 in each residualblock. The computational (Mult-Add operations) complexity is a constant scaling ofparameter numbers when we fix the input patch size. To have same complexity w 2 1= ˆw1 × wˆ2 = r × wˆ1 2 √, the residual identity mapping pathway need to be slimmedas a factor of r and the activation can be expanded with √ r times meanwhile. This simple idea forms our first widely-activated SR network WDSR-A. Experiments show that WDSR-A is extremely effective for improving accuracy of SISR when r isbetween 2 to 4. However, for r larger than this threshold the performance drops quickly. This is likely due to the identity mapping pathway becoming too slim. For example, in our baseline EDSR (16 residual blocks with 64 filters) for ×3 superresolution, when r is beyond 6, w1 will be even smaller than the final HR imagerepresentation space S 2 ∗3 (we use pixel shuffle as up sampling layer) where S is thescaling factor and 3 represents RGB. Thus, we seek forparameter-efficient convolution to further improve accuracy and efficiency with wider activationSRGAN-In SISR the aim is to estimate a high-resolution, super resolved image I SRfrom a low-resolution input image I LR. Here I LR is the low-resolution version of itshigh-resolution counterpart I HR. The high-resolution images are only availableduring training. In training, I LR is obtained by applying a Gaussian filter to I HRfollowed by a down sampling operation with down sampling factor r. For an imagewith C color channels, we describe I LR by a real-valued tensor of size W × H × Cand I HR, I SR by rW × rH × C respectively. Our ultimate goal is to train a generatingfunction G that estimates for a given LR input image its corresponding HR

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counterpart. To achieve this, we train a generator network as a feed-forward CNNGθG parametrized by θG. Here θG = {W1:L; b1:L} denotes the weights and biases of a L-layer deep network and is obtained by optimizing a SR-specific loss function l SR. For training images I HR n , n = 1, . . . , N with corresponding I LR n , n = 1, . . . , N, we solve: ˆθG = arg min θG 1 N X N n=1 l SR(GθG (I LR n), IHR n) (1) In this work we will specifically design a perceptual loss l SR as a weighted combination of several loss components that model distinct desirable characteristics of the recovered SR image.

[0022] The many features and advantages of the invention are apparent from the detailed specification, and thus, it is intended by the appended claims to cover all such features and advantages of the invention which fall within the true spirit and scope of the invention. Further, since numerous modifications and variations will readily occur to those skilled in the art, it is not desired to limit the invention to the exact construction and operation illustrated and described, and accordingly, all suitable modifications and equivalents may be resorted to, falling within the scope of the invention.