Image Interpolation with Adaptive K-Nearest Neighbours Search and Random Non-Linear Regression

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Abstract— *Learning-based image interpolation methods have been proved to be effective in image interpolation. In this study, the authors propose an accurate image interpolation with adaptive k-nearest neighbor searching and non-linear regression. The proposed method aims to find k-nearest neighbors of the input image patch and use them to learn the non-linear mapping between low-resolution and high-resolution image patches. To be specific, they first divide the training image patches into many subspaces, and then they utilize an adaptive robust and precise k nearest neighbor searching scheme with proposed normalized Gaussian similarity to find the k nearest neighbors in the matched subspace. The selected k image patch pairs are then used to learn the non-linear regression model through an extreme learning machine. Furthermore, the proposed interpolation method is a cascade framework that consists of two stages. Stage 2 takes the results of Stage 1 as input to further improve the performance.*

I. INTRODUCTION

Image interpolation refers to generating a corresponding high-resolution (HR) image that retains sharp edges and rich textures from an observed low resolution (LR) image. Existing image interpolation techniques can be sorted into three categories: polynomial-based methods, edge-directed methods. The traditional polynomial-based interpolation methods, such as bilinear, bicubic and cubic-spline interpolation, make use of the known pixel values to build a continuous interpolation function and then interpolate the missing pixels by re-sampling it. These methods do well in smooth images and achieve real-time performance. Image interpolation relates to methods of constructing new image detail from a discrete set of known points resulting in a high-resolution image. The problem is ill-posed, and the quality of the solution is usually considered subjectively, focusing on edges, texture, and clarity of content. Such properties can be generated in a number of ways, but to obtain them, new or assumed information must be introduced. Usually, the first crucial step of these methods is to estimate the direction of the edge in an HR image from its LR counterpart. However, it is usually inaccurate, especially in the regions with complex edges and textures. According to the resolution invariant property of edge orientation, Li and Orchard proposed a method called new edge-directed interpolation (NEDI) that uses the local covariance characteristics in LR image to estimate local covariance in HR image.

1.1 Image Interpolation

At an early stage of research, non-adaptive methods such as nearest, bilinear and bicubic interpolation methods were developed for digital image interpolation purposes. Those traditional methods were markedly different in image resolution, speed, and theoretical assumptions (i.e., theory of spatial variability). To the best of my knowledge, most of the assumptions applied today reduce interpolated image resolution due to the lowpass filtering process involved into their new value creative operations. However, the nearest neighbor assumption does not permit to create a new value, instead set the value at the empty location by replicating the pixel value located at the shortest distance. The effect of this is to make image pixel bigger which results in heavy jagged edges thus making this algorithm more inappropriate for applications requiring a H.R image (to accomplish certain tasks). A solution to such jaggedness was achieved through the bilinear interpolation. A bilinear based algorithm generates softer images but blurred thus making the algorithm inappropriate also for H.R. applications. The blurredness problem was reduced by introducing the convolution-based techniques. Such algorithms performed better than the two in terms of the visual quality but are also inappropriate to use where the speed is of the prime importance. Now, since the source image resolution is often reduced after undergoing the interpolation process, the easy way to generate a H.R. image using linear interpolation means is to reduce, at any cost, any operation.

1.2 Image Interpolation Methods

- Nearest neighbour.
- S Bilinear interpolation.

- Bicubic interpolation.
- Basic-splines (B-spline).
- Lanczos interpolation.

1.3 Nearest Neighbour

Nearest neighbor: It is a simplest interpolation. In this method each interpolated output pixel is assigned the value of the nearest sample point in the input image. The interpolation kernel for the nearest neighbor. Although this method is very efficient, the quality of image is very poor. It is because the Fourier Transform of a rectangular function is equivalent to a $sinc$ function; with its gain in pass band falls off quickly. Also, it has prominent side lobes are in the logarithmical scale.

1.4 Bilinear Interpolation

Bilinear interpolation is used to know values at random position from the weighted average of the four closest pixels to the specified input coordinates, and assigns that value to the output coordinates. The two linear interpolations are performed in one direction and next linear interpolation is performed in the perpendicular direction.

1.5 Bicubic Interpolation

The bicubic interpolation is advancement over the cubic interpolation in two-dimensional regular grid. The interpolated surface is smoother than corresponding surfaces obtained by above mentioned methods bilinear interpolation and nearest-neighbor interpolation. It uses polynomials, cubic, or cubic convolution algorithm. The Cubic Convolution Interpolation determines the grey level value from the weighted average of the 16 closest pixels to the specified input coordinates, and assigns that value to the output coordinates, the first four one-dimension. For Bicubic Interpolation (cubic convolution interpolation in two dimensions), the number of grid points needed to evaluate the interpolation function is 16, two grid points on either side of the point under consideration for both horizontal and perpendicular direction Fast and effective image copy-move forgery detection via hierarchical feature point matching.

1.6 Basic-Splines (B-Spline)

The nearest neighbor and Bilinear interpolations compromise the quality of image over efficiency due to rectangular shape in the pass band and infinite side lobes. The B-spline interpolations smoothly connects polynomials with pieces. A B-spline of degree n is derived through n convolutions of the box filter, Bsp0. Thus B-spline of degree 1 can be represented as Bsp1=Bsp0*Bsp0. The second-degree B-spline B2 is produced by convolving Bsp0*Bsp1 and the cubic B-spline Bsp3 is from convolving Bsp0*Bsp2.

1.7 LANCZOS INTERPOLATION

Lanczos filter is used to interpolate the value of a digital signal between its samples. It maps each sample of the given signal to a translated and scaled copy of the Lanczos kernel. Lanczos kernel is a sinc function windowed by the central hump of a dilated sinc function. Lanczos resampling used to increase the sampling rate of a digital signal. Lanczos kernel is the normalized sinc function sinc(x), windowed by the Lanczos window is used.

II. LITERATURE REVIEW

[1] AUTHOR NAME: Beijing Yang, W., Liu, (2018)

TITLE: Variation learning guided convolution network for image interpolation

DESCRIPTION: In this article, we implemented a variation learning model that effectively exploits the structural similarities for image representation, and construct a deep network based on this model for image interpolation. Based on the local dependency, our learning model represents an image as the three-dimensional features. Besides two coordinate dimensions, an additional neighbouring variation dimension is added to encode every pixel as the variation to its nearest low-resolution pixel by the local similarity. This added dimension lowers the risk of over-fitting for learning approaches and constructs abundant structural correspondences for inferring the missing information lost in image degradation. Then, these three-dimensional features are naturally modelled, extracted and refined by an end-to-end trainable recurrent convolution network for image interpolation. Comprehensive experiments demonstrate that our method leads to a surprisingly superior performance and offers new state-of-the-art benchmark.

[2] AUTHOR NAME: Zhu (2017)

TITLE: MMSE-directed linear image interpolation based on nonlocal geometric similarity

DESCRIPTION: In this article, we demonstrated a minimum mean square error (MMSE) directed linear interpolation to compose the high-resolution image from a single low-resolution image. We build up our interpolation model by using some similar image patches selected according to the nonlocal geometric similarity. First, we use a two-stage search scheme to collect the matched patches inside the whole image. Second, a similarity scaling factor is used in the second search to refine the collected patches so as to help find a robust solution to the MMSE-directed interpolation. Third, our MMSE-directed interpolation is regularized by the involved reference patches to make the solved interpolation coefficients more reliable. Experimental results show that our proposed method outperforms the state-of-the-art MMSE-directed linear interpolation schemes and works competitively with the state-of-the-art learning-based ones.

[3] AUTHOR NAME: Zhou, W., Li, X., Reynolds (2017)

TITLE: Nonlinear image interpolation via deep neural network

DESCRIPTION: In this article, the paper implemented the various adaptive image interpolation methods have been develop aiming at better recovering important image structures such as edges and textures. However, those methods are all based on an implicit assumption about the linear relationship between LR and HR pixels partially due to the difficulty with modelling nonlinear relationship. In this paper, we propose to take an explicit learning-based approach toward modelling the nonlinear relationship between LR an HR pixels. A six-layer convolution neural network with rectified linear units (ReLU) is presented and trained to learn the targeted nonlinear mapping from training data for image interpolation. Our experimental results have shown the proposed learning-based approach is often capable of achieving superior performance both subjectively and objectively to existing model-based methods.

[4] AUTHOR NAME: Zhu, S., Zeng, B., Zeng, (2016)

TITLE: Image interpolation based on non-local geometric similarities and directional gradients

DESCRIPTION: In this article, the paper demonstrated the robust interpolation scheme by using the nonlocal geometric similarities to construct the HR image. In our proposed method, the MMSE-based interpolation weighting coefficients are generated by solving a regularized least squares problem that is built upon a number of dual-reference patches drawn from the given LR image and regularized by the directional gradients of these patches. Experimental results demonstrate that our proposed method offers a remarkable quality improvement as compared to some state-of-the-art methods, both objectively and subjectively.

[5] AUTHOR NAME: Huang, J.J., Siu, W.C (2015)

TITLE: Fast image interpolation via random forests

DESCRIPTION: In this article, the paper proposes a two-stage framework for fast image interpolation via random forests (FIRF). The proposed FIRF method gives high accuracy, as well as requires low computation. The underlying idea of this proposed work is to apply random forests to classify the natural image patch space into numerous subspaces and learn a linear regression model for each subspace to map the low-resolution image patch to high-resolution image patch. The FIRF framework consists of two stages. Stage 1 of the framework removes most of the ringing and aliasing artifacts in the initial bicubic interpolated image, while Stage 2 further refines the Stage 1 interpolated image. By varying the number of decision trees in the random forests and the number of stages applied, the proposed FIRF method can realize computationally scalable image interpolation. Extensive experimental results show that the proposed FIRF(3, 2) method achieves more than 0.3 dB improvement in peak signal-to-noise ratio over the state-of-the-art nonlocal autoregressive modeling (NARM) method. Moreover, the proposed FIRF(1, 1) obtains similar or better results as NARM while only takes its 0.3% computational time.

Problem Definition

Image interpolation, which is a kind of image super-resolution, is a classic and challenging research topic in image processing. It has been used in many applications, such as surveillance, image and video resizing, medical imaging and so on. Image interpolation refers to generating a corresponding high-resolution (HR) image that retains sharp edges and rich textures from an observed low resolution (LR) image. In our Existing method, the image interpolation techniques can be sorted into three categories: polynomial-based methods, edge-directed methods and learning-based methods. The deep laplacian pyramid super resolution directly extracts features from the LR image to reduce computational load and then reconstruct the sub-band residuals of HR images by the deep Laplacian Pyramid convolutional network. The Variation learning modeled by an end-to-end recurrent convolutional network, represents an image as 3D features for image interpolation.

Drawbacks

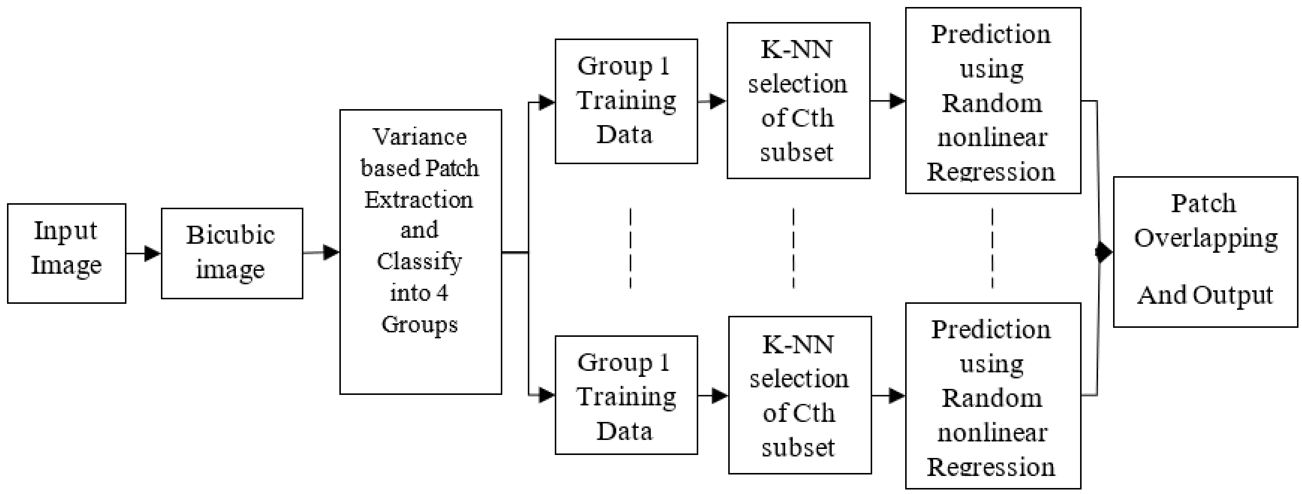
- These deep learning methods require GPUs and days to train the networks. They often depend on a large number of training data to obtain good performance.
- Suffer from artefacts on small edges of which directions are hard to estimate

III. PROPOSED METHOD

This paper propose an image interpolation algorithm based on adaptive *k-nearest neighbours search and non-linear regression* (AKNR), which belongs to traditional learning-based image interpolation. The selected *K nearest HR-LR* image pairs are then used to learn the non-linear regression models based on ELM.

Advantages

- Best performance on several image sets both in terms of qualitative and quantitative compared with other method
- Our method can outperform some deep learning methods when training data is limited.



3.1 Input Data

A collection data can be taken is obtained in the input image. Filtering concept is used in the input data to remove the noises in the image. A input data is given to the Image Interpolation to process the further step in this model.

3.2 Image Interpolation

Image interpolation relates to methods of constructing new image detail from a discrete set of known points resulting in a higher resolution image. The problem is ill-posed, and the quality of the solution is usually considered subjectively, focusing on edges, texture, and clarity of content. These properties can be generated in a number of ways, but to obtain them, new or assumed information must be introduced. Bicubic Image technique is used in the Image Interpolation.

3.3 Bicubic Image

Input image is applied to Bicubic image. In the image interpolation process, the input LR image is first interpolated to the same size as the HR image using bicubic interpolation. The resulting image is then divided into overlapping patches for reconstruction. Only edge patches with edges and textures will be interpolated and smooth patches are excluded since on which bicubic performs well. For each collected input patch, we classify it into the nearest cluster *Ct* and find the *k* nearest neighbours for it in cluster *Ct*. After learning the model parameters, the final reconstructed HR patch can be obtained easily. Therefore, the overall peak signal-to-noise ratio (PSNR) performance of an interpolated image is almost the same, with a difference of no more than 0.01 db. Finally, the target interpolated HR image is reconstructed by averaging the overlapped reconstructed HR patches to avoid the block effect and preserve consistency between neighbouring pixels.

3.4 Variance Based Patch Extraction

Variance based extraction is a measure of the amount of variance that is captured by a construct in relation to the amount of variance due to measurement error. A collection of data's can be obtained in the variance-based patch to extract the feature used KNN selection model of the Cth subset of model. Further, they predict the image of the prediction method by using Random Non-linear Regression.

3.5 Random non-linear regression model

We can learn more accurate mappings than the ones learned by linear regression. Here the use nonlinear learning algorithm based on the ELM. It is implemented with single hidden layer feed-forward neural networks (SLFNs) to learn nonlinear mappings. The ELM can provide a learning-based feature mapping that can be applied in regression. ELM also tend to attain wonderful generalisation performance as well as fast speed.

3.6 Patch Overlap and Output Image

Using a patch-based approach in image processing simply means the image is divided into these small patches and each patch is then processed individually. After the processing steps done in the patch overlap of the model. Then, final output image is reconstructed out of the individually processed patches display the output image of the model.

IV. APPLICATION AND FUTURE ENHANCEMENT

4.1 Applications of Digital Image Processing

- Image sharpening and restoration
- Medical field
- Machine/Robot vision
- Pattern recognition

4.2 Image sharpening and restoration

Image sharpening and restoration refers here to process images that have been captured from the modern camera to make them a better image or to manipulate those images in way to achieve desired result. It refers to do what Photoshop usually does. This includes Zooming, blurring, sharpening, gray scale to color conversion, detecting edges and vice versa, Image retrieval and Image recognition.

4.2.1 Medical field

The common applications of DIP in the field of medical is Gamma ray imaging, PET scan, X Ray Imaging, Medical CT, UV imaging.

4.2.2 Machine/Robot vision

Many challenges that a robot face today, one of the biggest challenges still is to increase the vision of the robot. Make robot able to see things, identify them, identify the hurdles etc. Much work has been contributed by this field and a complete other field of computer vision has been introduced to work on it.

4.2.3 Pattern recognition

It involves the study of image processing, it is also combined with artificial intelligence such that computer-aided diagnosis, handwriting recognition and images recognition can be easily implemented. Now a days, image processing is used for pattern recognition.

4.3 Video processing

A video is nothing but just the very fast movement of pictures. The quality of the video depends on the number of frames/pictures per minute and the quality of each frame being used. Video processing involves noise reduction, detail enhancement, motion detection, frame rate conversion, aspect ratio conversion, color space conversion etc.

4.3.1 Object recognition using SIFT features

Given SIFT's ability to find distinctive key points that are invariant to location, scale and rotation, and robust to affine transformations (changes in scale, rotation, shear, and position) and changes in illumination, they are usable for object recognition.

4.4 Robot localization and mapping

In this application, a trinocular stereo system is used to determine 3D estimates for key point locations. Key points are used only when they appear in all 3 images with consistent disparities, resulting in very few outliers. As the robot moves, it localizes itself using feature matches to the existing 3D map, and then incrementally adds features to the map while updating their 3D positions using a Kalman filter. This provides a robust and accurate solution to the problem of robot localization in unknown environments. Recent 3D solvers leverage the use of key point directions to solve trinocular geometry from three key points and absolute pose from only two key points, an often disregarded but useful measurement available in SIFT. These orientation measurements reduce the number of required correspondences, further increasing robustness exponentially.

4.5 Analyzing the Human Brain in 3D Magnetic Resonance Images

The Feature-based Morphometry (FBM) technique uses extrema in a difference of Gaussian scale-space to analyze and classify 3D magnetic resonance images (MRIs) of the human brain. FBM models the image probabilistically as a collage of independent features, conditional on image geometry and group labels, e.g. healthy subjects and subjects with Alzheimer's disease (AD). Features are first extracted in individual images from a 4D difference of Gaussian scale-space, then modeled in terms of their appearance, geometry and group co-occurrence statistics across a set of images. FBM was validated in the analysis of AD using a set of ~200 volumetric MRIs of the human brain, automatically identifying established indicators of AD in the brain and classifying mild AD in new images with a rate of 80%.

4.6 3D scene modeling, recognition and tracking

This application uses SIFT features for 3D object recognition and 3D modeling in context of augmented reality, in which synthetic objects with accurate pose are superimposed on real images. SIFT matching is done for a number of 2D images of a scene or object taken from different angles. This is used with bundle adjustment initialized from an essential matrix or trifocal tensor to build a sparse 3D model of the viewed scene and to simultaneously recover camera poses and calibration parameters. Then the position, orientation and size of the virtual object are defined relative to the coordinate frame of the recovered model. For online match moving, SIFT features again are extracted from the current video frame and matched to the features already computed for the world mode, resulting in a set of 2D-to-3D correspondences. These correspondences are then used to compute the current camera pose for the virtual projection and final rendering. A regularization technique is used to reduce the jitter in the virtual projection. The use of SIFT directions have also been used to increase robustness of this process. 3D extensions of SIFT have also been evaluated for true 3D object recognition and retrieval.

4.7 Future Enhancement

Multimedia image information is often used as evidence in many important occasions, such as criminal investigations and military scenarios. However, with the development of technology and network, digital images can be easily acquired and tampered with, which makes the authenticity of digital images face serious risks and poses a great threat to Judicial Forensics and various research and future work.

V. CONCLUSION

In this paper, we propose an image interpolation algorithm based on adaptive k-nearest neighbors search and non-linear regression (AKNR), which belongs to traditional learning-based image interpolation. The proposed AKNR method outperforms the state of-the-art methods and achieves competitive results with deep learning methods on different datasets. For training, our method divides the training edge patches into four groups and employs a clustering method roughly separate each group into many subsets. For interpolation, it first conducts the adaptive precise search using the proposed NGS measurement metric. The selected K nearest HR-LR image pairs are then used to learn the non-linear regression models based on ELM. Finally, the output HR patch is effectively reconstructed by the learned non-linear regression. The framework of our method is two-stage cascaded. The proposed method realizes the best performance on several image sets both in terms of qualitative and quantitative results in the comparison methods. Meanwhile, our method can outperform some deep learning methods when training data is limited.

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