A Review on Various Image Interpolation Techniques

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Abstract – *The need for image interpolation is rapidly growing in the new world where the use of display devices are frequently increasing. In today's world the people need pleasing visual quality as the use of display devices like in evitable mobile phones, handheld cameras and high definition monitors are grown to its peak. Therefore it is a significant area of research. It's importance stands up when come into computer graphics where it is needed for file compression and expansion. Application of image interpolation includes medical diagnostic imaging, surveillance cameras and even advanced autonomous driving. Image interpolation methods existing can be classified into three: conventional polynomial based methods, edge directed methods, learning based methods. This paper mainly focuses on reviewing various types of image interpolation techniques with an intention that this paper will be useful for researchers interested in image interpolation field.*

Key Words: Image interpolation, display devices, conventional polynomial based methods, edge focussing methods, learning based methods.

1.INTRODUCTION

The technology for display devices are rapidly increasing today. Also people are frequently interfering with medias with taking selfies and pictures, posting their pictures through media in online for seen by their friends and family whom take part in social networks like tweeter, facebook and in mobile applications like Whatsapp etc. Also people find joy in seeing pleasing visuals as it gives mind an extra energy. Inorder to meet people's requirements different image processing techniques are needed. Among the different image processing techniques image interpolation stands as a prior method. There are different image processing areas where those are performed after performing image interpolation. Moreover there are different areas where image interpolation is the pivot point like surveillance cameras, medical diagnostic imaging and file compression. In surveillance cameras positioned at a fixed point the images received from farther points cannot be identified visually without proper zooming. Medical diagnostics need viewing finer particles for operating in human body. Image interpolation methods existing can be classified into three:

1).Polynomial based methods

2).Edge directed methods

3).Learning based methods

The learning based methods can be again divided into two:

a)Traditional learning based methods

b)Deep learning based methods

2. POLYNOMIAL BASED METHODS

This method consists of easiest and conventional methods. They are Bilinear interpolation method, Bicubic interpolation method and Nearest neighbour interpolation method. The computation involved in these methods are simple when compared to other interpolation methods. These methods utilize the pixel values already given to generate a continous interpolation function and then by resampling missing pixels in between. These methods provide good results in smooth regions and real time performance is attained.

2.1 Bilinear interpolation

Bilinear interpolation functions by taking weighted average of the adjacent 4 neighborhood pixels to compute its interpolated result. The final image is much smoother image when compared with the original image. Here if all known pixel distances are of equal units, then the resulting interpolated value is just their sum divided by four. In this method interpolation is performed in both directions horizontal and vertical. This method provide better result when compared to nearest neighbor interpolation and the computation time is less when compared with bicubic interpolation.

2.2 Bicubic interpolation

Bicubic interpolation can be considered as the best method among the traditional polynomial methods. Bicubic interpolation functions by taking weighted average of the adjacent 16 neighbourhood pixels to compute its interpolated result. These pixels are located at different distances from the assuming unknown pixel. The nearest pixels are given higher value in weighting during the calculation. Bicubic interpolation results sharper images than the previous described two methods. This method provides better result but the computational time is longer. This method is the best method among all traditional methods at the condition where time is not a matter of concern.

2.3 Nearest neighbour interpolation

Nearest neighbour interpolation is the most basic interpolation method and it needs less processing time among all these traditional interpolation methods. In this method the resulting pixel is obtained by replacing with the nearest pixel. Nearest neighbor interpolation is considered to be a simple method of interpolation. It is easy for implementing. It provides good result when the image contains high resolution pixels. In this method some information presented at the edges were lost.

3. EDGE DIRECTED METHODS

These methods performs interpolation by interpolating the missing pixels along the edge other than across the edge. The first significant step in these methods are determining the direction of edges in the high resolution image. These methods consider edge information and texture. The traditional methods produce edges as blurring and also artefacts near the edges. These methods take more computational time than traditional methods.

3.1. New edge directed interpolation method(NEDI)

While considering the edge orientation resolution invariant property this method utilizes the local covariance characteristics present in the low resolution image to evaluate local covariance that might have present in the high resolution image. Covariance correspondence is used here. It instantaneously evaluates local covariance characteristics and utilize them to determine the ideal linear MMSE prediction. High resolution covariance can be simply replaced with low resolution covariance here which is possible because both contains contain the information about the same edge orientation.

3.2. Soft decision interpolation methods(SAI)

This uses a two dimensional piece-wise autoregressive model to evaluate the missing pixels. Other than considering single pixel at a time here evaluates missing pixels as a group. Linear transformation function is taken from calculated samples in low resolution image to non-calculated points in high resolution image that is to be interpolated. The function will be defined for each and every point but not shared to all data points in the training window. Thus it is called as local linear regression.

Moving weights are taken here. Weight is proportional to similarity between correspondence of local neighbourhood of the pixel being processed and the neighbourhood of other image pixels. MLS(Moving least square) is used here. It is different from that of OLS(ordinary least square). It considers all samples in the training window with similar importance even in the case where local neighbourhood is at the boundary.

3.3 Interpolation based on non-local geometric similarities

It uses non-local geometric similarities between the corresponding high and low resolution image patches to generate high resolution image. For selecting the similar image patches here uses non-local geometric similarity. In this method ,the MMSE(minimum mean square error) based interpolation is used. Weighting coefficients are created by solving regularized least square problem which is set on many dual reference patches taken from already given low resolution image. Then regularized by directional gradients of the already taken patches. Non-local geometric similarity is utilized to collect samples for this model. Thus the model is more stable. By solving algebraic equations interpolation weighting coefficients are determined. The equations are created from reference patches by scaled Euclidean distance .It is based on similarity and measurement. Other than feature based methods in which low resolution and high resolution features are taken to estimate missing pixels, here consider geometric similarity.

4. LEARNING BASED METHODS

The results of edge directed methods consists of artefacts along small edge of which direction will be hard to approximate. So there comes learning based methods. Their promising results lead to attain a lot of attention now a days. These are further classified into two: 1)Traditional learning based methods 2)Deep learning based methods. The main idea behind this method is the usage of an external image database. The image database is used for learning mapping from low resolution patches to their corresponding high resolution patches.

4.1 Traditional learning based methods

These methods use traditional patch learning based methods. Some of them are discussed herewith.

4.1.1 Sparse representation model(SRM)

It creates sparse representation for each patch of low resolution input and then the coefficients of this representation are used to create high resolution output. Here K-SVD algorithm is used to learn an overcomplete dictionary. These are learned from natural image patches. Two coupled dictionaries ,high resolution and low resolution are used here. For sparse representation sparse solutions for system of linear equations are used. Here sparse considering polynomial equations which are lesser than unknowns. Dh and Dl are trained and contains some sparse representations for each low and high resolution patch pairs. Then mean pixel values for each patch are substracted thus make the dictionary represents image textures rather than absolute intensities. Then in the recovery process, for each high resolution image patch mean value is then predicted by its low resolution version. Sparse representation with respect to Dl are found for each input low resolution patch. The patches taken from the high resolution image can be denoted as sparse linear combination in the dictionary that is trained from high resolution patches which is further sampled from training images. The process mainly consists of mean pixel value calculation. Then solve optimization problem. Then find high resolution image by using gradient descent and closest patch is found.

4.1.2 Non-local autoregressive modelling(NARM)

It performs interpolation by incorporating image non-local self similarity into sparse representation model. Auto regressive model is used as it exploits image local correlation for interpolation. Whereas NARM(non-local auto regressive model) is a natural extension and generalization of the traditional ARM which uses spatially local neighbours only for image patches approximation. That is the pixel may have many similar non-local neighbours but spatially far from it. For approximation of image patches those non-local neighbours are used. Here clustering based learning of PCA sub dictionary is done. It consists of patch clustering, PCA dictionary computation, sparse coding and NARM computing. Because of this computational complexity is high. First coherence value between sampling matrix and different dictionaries are computed. Then by minimizing the energy function after updation of image patch and PCA dictionaries. Variable splitting technique is used for minimization. Augmented Lagrange Multiplier(ALM) is used for this. The data fidelity term will fail to impose structural constraint in the pixels missing in conventional SRM. But here this problem is addressed by utilizing non-local self similarity with NARM. Coherence between sampling matrix and dictionary can be reduced by NARM. Thus it is more effective. To regularize SRM minimization non-local redundancy is used. And for signal representation local PCA dictionary is utilised to span the sparse domain in an adaptive manner.

4.1.3 Fast image interpolation via random forest(FIRF)

Here random forests are applied for classifying natural image patches space. These are sorted into a number of subspaces and the high resolution and low resolution mapping are done by using linear regression. It provides high accuracy with low computation cost. In the case of edge directed methods computational speed is limited because of learning the interpolation model from the local image patches. While in SRM sparse representation for each patches is time consuming, besides in NARM algorithm complexity is high. Because of this problem traditional polynomial methods are used in commercial areas. In this method for effective learning random forests are used. Here the model searching process are simplified by just comparing various pairs of pixels for each and every image patch.

Here natural image patches are considered as a combination of multiclass of image patches. Here the assumption is that the image patches present in the same class constitute a linear subspace where the relationship between low resolution and high resolution image patches is modelled by linear mapping function. A combination of classification and regression processes are used for solving image interpolation in this method. The classification methods are: SVR(Support vector recognition), k-nn(k-nearest neighbour) and k-means clustering. SVR requires complex computation during both training and testing. where as k-nn method is time consuming. Here random forest is applied for fast image interpolation by recursive classification. These are classified into one leaf node by comparing with threshold in each non-leaf node and mapping low resolution patches to high resolution patches by linear regression models. It consists of set of decision treesin which each decision tree is recursively classified. And linear regression model stored in each leaf node input low resolution patch is lead to high resolution patch space.It achieves better generalization and higher stability when compared to single decision tree. Natural patch space is represented by a many linear regression models by separating whole training data. Binary tests are performed at non-leaf nodes to efficiently find matching linear regression model.Here first the given image is interpolated with bicubic interpolation to get the same size of the desired image. From these image patches containing edge patches are extracted and divided into 4 groups according to known pixel patterns. Then groups of image patches are passed into random forests which is learned using training data with same already known pixel patterns.

4.2. Deep learning based method

Now a days these methods are using mostly. These methods use deep neural networks. Some of them are discussed here. These methods requires GPUs for training and number of days are needed for training the model. Also large number of training data is needed.

4.2.1. SRCNN Super resolution using conventional neural network

In this method a deep convolutional neural network is utilized to directly learn an end to end mapping between the low resolution and high resolution images. A 7-layer dilated convolutional neural network (DCNN) with skip-connections is used in this method. This dilated convolutions allow the network to arbitrarily control the field-of-view of the network. By adjusting the dilation rate and different combination of contextual information using skip-connections performance and speed is achieved.

4.2.2. VDSR Very deep super resolution

In this method very deep convolutional neural networks are used by utilizing 20 layers for learning the residuals. Of the 20 weight layers are all identical exception for the first and last. The first layer is the input layer which takes in the single channel luminance of given input image. The total network then comprises of 18 convolutional layers, each of which has 64×3 × 3 filters, and each convolutional layer is followed next by a rectified linear unit (ReLu). The final layer then reconstruct the proposed residual image with a 3 × 3 × 64 filter. This final residual image is then combined with the low-resolution input to give out the resulting super-resolution output.

4.2.3 DRCN Deeply-Recursive Convolutional Network

This method uses deeply recursive mechanism for deepening convolutional neural networks thus boosting up the performance. This method consists of very deep recursive layer of 16 recursions. Learning a DRCN is very difficult with a standard gradient descent technique since it has exploding/vanishing gradients. For making easier the hardness of training, the method consists of two extensions they are recursive-supervision and skip-connection.

4.2.4 Lap SRN(Laplacian pyramid super resolution network)

In this method features are directly extracted from the low resolution image to lessen the computational load. Then the reconstruction of the sub band residuals of high resolution images by deep Laplacian pyramid convolutional neural network. There is no use of bicubic interpolation for extracting features from low resolution image input, the network successively reconstructs the sub-band residuals of high-resolution images at many pyramid levels, specifically at log2(S) levels.

REFERENCES

[1] Keys,R,"Cubic convolution interpolation for digital image processing"IEEE Trans.Acoust Speech Signal Process, 1981, 29 ,pp 1153-1160
[2] .Blu T Thevanaz,P Unser,M "Linear interpolation revitalized"IEEE Trans Image Process, 2004,13(5),pp 710-719
[3] Zhou, D., Shen, X., Dong, W.: "Image zooming using directional cubic convolution interpolation", IET Image Process,, 2012, 6, (6), pp. 627–634
[4] Li, X., Orchard, M.T.: "New edge-directed interpolation" IEEE Trans. Image Process., 2001, 10, (10), pp. 1521–1527.
[5] Liu, X.M., Zhao, D.B., Xiong, R.Q., et al: 'Image interpolation via regularized local linear regression', IEEE Trans. Image Process., 2011, 20, (12), pp. 3455–3469.
[6] Hung, K.W., Siu, W.C.: 'Fast image interpolation using the bilateral filter', IET Image Process., 2012, 6, (7), pp. 877–890.
[7] Zhang, X.J., Wu, X.L.: "Image interpolation by adaptive 2-D autoregressive modeling and soft-decision estimation", IEEE Trans. Image Process., 2008, 17, (6), pp. 887–896.
[8] Hung, K.W., Siu, W.C.: 'Robust soft-decision interpolation using weighted least squares', IEEE Trans. Image Process., 2012, 21, (3), pp. 1061–1069
[9] Giachetti, A., Asuni, N.: 'Real-time artifact-free image upscaling', IEEE Trans. Image Process., 2012, 21, (4), pp. 2361–2361.
[10] Zhu, S., Zeng, B., Zeng, L., et al: 'Image interpolation based on non-local geometric similarities and directional gradients', IEEE Trans. Multimedia, 2016, 18, (9), pp. 1707–1719.
[11] Zhu, S.Y., He, Z.Y., Liu, S.C., et al: 'MMSE-directed linear image interpolation based on nonlocal geometric similarity', IEEE Signal Process. Lett., 2017, 24, (8), pp. 1178–1182.
[12] Ni, K.S., Nguyen, T.Q.: 'An adaptable k-nearest neighbors algorithm for MMSE image interpolation', IEEE Trans. Image Process., 2009, 18, (9), 1382–1394.
[13] Dong, W., Zhang, L., Lukac, R., et al: 'Sparse representation based image interpolation with nonlocal autoregressive modeling', IEEE Trans. Image Process., 2013, 22, (4), p. 1382.
[14] Huang, J.J., Siu, W.C., Liu, T.R.: 'Fast image interpolation via random forests', IEEE Trans. Image Process., 2015, 24, (10), pp. 3232–3245.
[15] Dong, C., Loy, C.C., He, K., et al: 'Image super-resolution using deep convolutional networks', IEEE Trans. Pattern Anal. Mach. Intell., 2016, 38, (2), pp. 295–307.
[16] Kim, J., Lee, J.K., Lee, K.M.: 'Deeply-recursive convolutional network for image super-resolution'. 2016 IEEE Conf. on Computer Vision and Pattern Recognition, Las Vegas, USA, June 2016, pp. 1637–1645.
[17] Zhou, W., Li, X., Reynolds, D.S.: 'Nonlinear image interpolation via deep neural network'. 2017 51st Asilomar Conf. on Signals, Systems, and Computers, Pacific Grove, USA, October 2017, pp. 228–232.
[18] Lai, W.S., Huang, J.B., Ahuja, N., et al: 'Deep laplacian pyramid networks for fast and accurate super-resolution'. 2017 IEEE Conf. on Computer Vision and Pattern Recognition, Honolulu, USA, July 2017, pp. 624–632
[19] Yang, W., Liu, J., Xia, S., et al: 'Variation learning guided convolutional network for image interpolation'. IEEE Int. Conf. on Image Processing, Beijing, China, September 2018, pp. 1652–1656.