Image Super-Resolution Based On Single Frame GPS Technique

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Abstract —SingleImage Super-resolution (SR) technique is based on extracting non-redundant information from a single low resolution image to obtain corresponding high resolution image. Since the problem is unpredictable, an effective, efficient and robust algorithm is required to augment the image resolution. The technique proposed through this paper focuses on image resolution enhancement based on the Gradient Profile Sharpness (GPS) metric. The GPS ratio value for a given gradient profile is obtained by applying two gradient approximation models i.e. the Triangle model and the Two-term Gaussian model. These two models describe the gradient profile shape for sharp and smooth edges respectively. The transformation of GPS of the decimated image to the high resolution grid is formulated. The transformed GPS is then added as a prior to the High Resolution image reconstruction model to obtain the HR image. The proposed methodology not only increases the spatial resolution, but also conserves the shape of gradient profile for every edge pixel, thus protecting the information of the original image.

Index Terms — Single ImageSuper-resolution, Gradient profile, Triangle model, Two-term Gaussian model, GPS

I. INTRODUCTION

Single Image Super-resolution technique is based on exploiting information of a single low resolution image grid to obtain corresponding high resolution image grid through software based image processing techniques. The details contained in an image are represented by its resolution. As the resolution or the density of pixels in an image is increased, optimum and accurate information can be obtained from the image. This paper describes the need and development of a spatial domain image super-resolution algorithm termed as Gradient Profile Sharpness (GPS) technique. The aim of the technique is to up-scale a LR grid along with conservation of edge sharpness and edge contrast parameters of the image.

In the modern digital applications, high resolution images are usually desired for further analysis, processing and optimum information extraction. The degradation of an image may be caused due to reasons such as compression, optical blurring, motion or shake of the acquisition device, absence of sharp edges, etc. The principal areas of applications of super-resolution are to improve the human perception and interpretation by adding useful pictorial information and to improve the quality of image representation for automated machining systems. The domains of application of super-resolution include medical imaging, satellite imaging, video surveillance,navigation and positioning, multimedia, land surveys, microscopy imaging, forensic science, etc. The Modern Digital Communication systems including cloud computing etc. tend to store the images in the cloud storage in their decimated forms. Thus to retrieve them back to their original resolution, super-resolution is required. One such technical advancement is IOT based medical system wherein, data of the patients is stored on cloud, and can be retrieved whenever required using biometric security system.

II. LITERATURE SURVEY

The principle classification of resolution of digital images is Spatial Resolution andGray level (Pixel) resolution. The spatial resolution of an image is limited by the image acquisition system, designed using sensors which are typically CMOS pixel sensors or CCD (Charge Coupled Devices). To increase the spatial resolution of an image during acquisition, it is required to increase the number of sensors and reduce their size. However, as the sensor size would be reduced, the light incident on the sensor decreases which further leads to shot-noise formation and reduces the SNR (Signal-to-Noise Ratio). Also, as the number of sensors is increased, the hardware cost also increases. The high frequency image details (related to the gray-level resolution) are limited by the optical lens blurs aperture diffraction effects of the acquisition device. Incorporating acquisition systems to capture high resolution images is thus very costly and impractical in real systems. A prominent solution is to accept the degradations in the image and use software based processing to acquire corresponding higher resolution image.

The methods of SR to be implemented depend on the type of application. The Super-resolution algorithms can be broadly classified as:

1. Multi-frame SR Algorithms

1. Interpolation based approach
2. Frequency domain approach
3. Regularization based approach

2. Single Image SR algorithms

1. Learning (Example) based approach
2. Reconstruction based approach

In the Multi-frame SR technique [2], [3], [5], [9], [10], multiple LR images of the same scene in 'different looks' are captured and using sub-pixel shifts in the LR image, super-resolution is acquired. The interpolation based approach [2], [5], [9] works on the principle of constructing a HR image by projecting all the acquired LR images to a reference image. Frequency-domain-based approach is based on the principle that the high frequencies are spread across the multiple LR images in the form of aliased spectral frequencies. Regularization based approach [10] is based on the principle to incorporate prior info about the unknown HR image.

Single image SR [1], [4], [6], [7], [8] is a more sophisticated process which artificially synthesizes new information or details in the image from a single input LR image. The Learning based approach [4], [6], [7] develops machine learning techniques and often employs a dictionary generated from an image database. Reconstruction based approach [1] do not use a training set but define constraints for the target HR image to improve the quality of the reconstruction.

To enhance the resolution of an image, the contrast of the edge along its gradient direction must be maintained. In this paper, a spatial domain single image super-resolution technique termed as GPS is developed which not only extends the profiles, but also maintains its original profile characteristics. To accurately describe and conserve the shapes of the gradient profiles of the edge pixels, two models are formulated i.e. the Triangle model and the Two-term Gaussian model.

III. FORMULATION OF THE PROBLEM

In various medical situations, a patient may opt for a scan test only once because of financial reasons or health issues. Thus, to overcome such situations, an algorithm to estimate HR image precisely from a single LR is developed. The proposed framework focuses on image resolution enhancement GPS technique of SR reconstruction based on the gradient magnitudes of an edge pixel in its corresponding gradient direction. GPS is a reconstruction based single Image SR algorithm applied in spatial domain, which predominantly focuses on spatial augmentation as well as edge sharpness and contrast retention.

A. GRADIENT PROFILE DESCRIPTION

The Gradient profile along a direction in an image is One-Dimensional information which represents the respective gradient magnitudes of the pixels which are a part of the profile. In the proposed system, we are interested to conserve the gradient profiles of the edge pixels i.e. preserve the shape of the profile and acquire augmentation. Thus, the gradient profiles considered for enhancement are different for every edge pixel and these profiles are directed in the direction of maximum change in gradient.

The gradient magnitude and gradient directions for the pixels can be obtained using the predefined function 'imgradient' in MATLAB.

By plotting the gradient profiles for respective edge pixels, the sharpness or smoothness of the edge can be determined. Here, in this method we consider that if pixels less than or equal to eight are a part of profile for a given edge pixel in the image, then it would be considered to be a sharp edge, otherwise if number of pixels is greater than eight, then it would be considered to be a smooth edge.

The obtained edge gradient profiles however differ in shape, symmetry and the number of pixels which are a part of the respective profile. Thus to represent these gradient profiles, we two basic approximation models are developed which are flexible and may accurately fit the provided gradient profile of any given length. Using these models, the gradient profile shape can be fitted, preserved and later, the GPS is extracted to produce the HR grid.

The two models used to represent the gradient profiles of the edge pixels are:

1. The Triangle Model
2. The Two-term Gaussian model

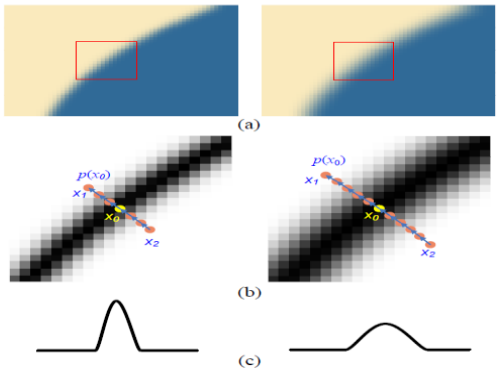


Fig. 1. (a)Visual perception of a sharp and smooth image resp. (b) Length of the corresponding gradient profiles at an edge pixel (c) The plot of gradient profile of a sharp and smooth edge pixel resp.

Each of the gradient profiles obtained have a pixel at which the gradient magnitude is maximum. This pixel of the profile is denoted as the 'peak' pixel of the profile. With respect to the 'peak' pixel in the profile the coordinate system representing the profile distance is normalized. Also, to improve flexibility in designing the algorithm, each of the gradient profiles is divided into two parts i.e. left side and right side with profile peak as the reference pixel of the profile.

These models are based on the ‘Least Squares Method’ of curve approximations to produce accurate curve representation and reduce fitting errors.

1. The Triangle Model

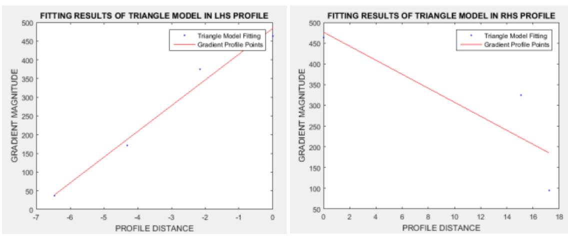
The approximation model is used to fit the gradient profiles of short length, i.e. here, the number of pixels which are part of the respective profile is less than or equal to eight. Such gradient profiles are termed as ‘short profiles’ or ‘profiles without tails’. These short profiles thus represent that the corresponding edge pixels constitute a sharp edge. Since, the profiles can be asymmetric, thus for obtaining accurate fitting results, we separately apply the model on the two corresponding sides of the profile peak.

To obtain the triangle model approximation, the slopes of the pixels present in the profile are calculated. The slope for both sides of the model is fitted or approximated separately to provide flexibility in the shape of the profiles retrieved from the image for attaining optimum profile representation. The slopes of both sides are normalized using the function ‘fit’ in MATLAB, which is based on the Least squares method of fitting.Further, each side of the profile is linearly represented in the form of the equation:

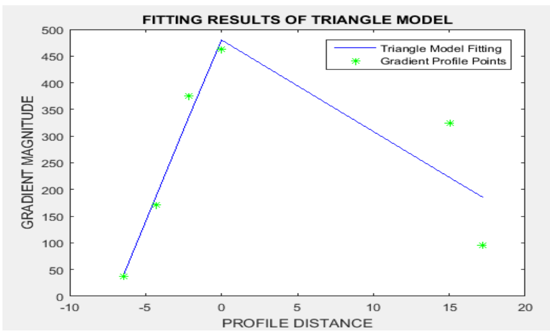
mag_T(x) ={ k*dx + h if value>0 (1)

{ 0 otherwise

Where,mag_T(x) represents the gradient magnitude of the pixel ‘x’ which is far from the profile peak by a profile distance denoted as ‘dx’. The normalized slope ‘k’ is different for the two sides of the approximation, and is independent of the other profile side.



(a) (b)



(c)

Fig. 2. (a)Fitting Results of Triangle model to the LHS profile.

(b) Fitting results of Triangle model to the RHS profile.

(c) Fitting results of the model to the profile.

2. The Two-term Gaussian Model

The approximation model is used to fit profiles of longer length, i.e. the number of pixels representing the corresponding profile is greater than eight. Such gradient profiles are termed as ‘long profiles’ or ‘profiles with heavy tails’ and are difficult and complicated to be accurately fitted. These profiles thus describe that the corresponding edge is a smooth edge. Thus, the Gaussian model provides an efficient tool for fitting such heavy tailed profiles. To improve the fitting results, we compute the two-term model.

Equation to represent gradient profile is derived as:

$$\text{mag\_G}(x) = \frac{a1}{b1\sqrt{(2\pi)}} e^{-((x-c1)^2)/2(b1^2)} + \frac{a2}{b2\sqrt{(2\pi)}} e^{-((x-c2)^2)/2(b2^2)}$$

If value > 0

= 0 otherwise (2)

Where, mag_G(x) represents the gradient magnitude of the pixel ‘x’ in the provided gradient profile. The features of the model are described by the above mentioned parameters: a1, a2, b1, b2, c1 and c2. The values of a1 and a2 correspond to the rates in which two Gaussian models are to be mixed. The values of b1, b2 represent the standard deviation; values of c1, c2 represent the mean values of the corresponding Gaussian models which are mixed to obtain optimum approximation of the gradient profile.

The above mentioned parameters are acquired using the function ‘lsqcurvefit’ or using the ‘fit’ function predefined in the Curve Fitting Toolbox in MATLAB software. The ‘fit’ function plots the approximated Gaussian mixture model and returns the values of the six estimation parameters which are necessary to be known for transformation of gradient profiles and thus to implement the SR algorithm.

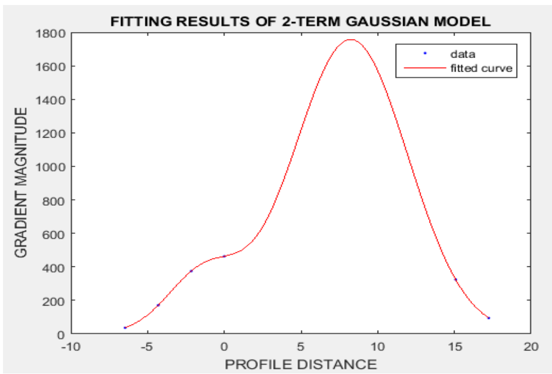


Fig. 3.Fitting results obtained by implementing the mixed Gaussian model

Thus, by implementing these two models for optimizing the fitting of respective gradient profiles, we obtain highly accurate descriptive profile characteristics, which are further used to obtain the GPS ratio and the transformation of LR to HR grid.

B. THE GPS RATIO

The important parameters which are extracted from the two gradient profile representation models are:

1. The height of the profile i.e. the gradient magnitude of the 'peak' pixel of the profile, denoted by 'h'. It is a measure of contrast at the provided edge.

2. The spatial scattering of the profile with respect to the profile distance between the two pixels present at the ends of the profile, denoted by 'd'. This feature is a measure of the profile distance over which the gradient profile is spread.

The GPS ratio (η) is defined as the ratio of the height to the spatial scattering of the provided gradient profile.

$\eta = h/d(3)$

The above equation states that the GPS super-resolution technique not only deals with spatial resolution augmentation, but also takes edge contrast preservation into consideration.A higher value of 'η' represents that the corresponding gradient profile is short in length and thus, the edge is sharp. However, a lower value of 'η' represents that the gradient profile is heavy tailed and thus the edge is smooth.

Thus, the GPS technique is robust as it provides flexible fitting for variable shapes of profiles and approximations to obtain the gradient profiles in the target field, i.e. the HR grid.

C. DERIVE GPS RATIO (η) TRANSFORMATION RELATION

To extract HR details from the provided LR image, a transformation of the GPS ratio of the gradient profiles is required. To formulate the relationship, the relation among the values of the GPS ratio for various upsizing values must be studied. Conventionally, the values of the up-sizing or up-scaling ratio denoted by 'R' are natural numbers, i.e.

R = 2, 3, 4, and so on. However, large values of the up-scaling ratio may tend to distort the image details due to excessive blurring of the edge pixels.

For a required up-scaling ratio, the GPS ratio pair for each gradient profile can be obtained which constitutes of GPS ratio of the profile in its LR form and the transformed GPS ratio to acquire a HR image.

D. HIGH RESOLUTION IMAGE RECONSTRUCTION

Through the GPS transformation metric, we obtain the transformation of gradient profiles from ones representing the profiles in LR grid to the ones which represent profiles in the target HR grid. Since GPS technique also incorporates preservation of shape of the gradient profiles and edge contrasts, thus some restrictions are proposed to the system in order to conserve the total energy in the form of shape of the gradient profile and the edge contrast during the transformation of the gradient profiles. The constraints are stated as:

1. The sum of the gradient magnitudes of the pixels of a gradient profile must remain consistent throughout the transformation of the gradient profiles.

2. The shape of the gradient profile must remain unchanged over the transformation. This is important because the shape represents the nature of the edge i.e. sharp or smooth.

3. The peak pixel assigned to every gradient profile must remain unchanged after the transformation. This constraint avoids the possibility of shifting of edges.

On the basis of the above restrictions, HR image reconstruction models are proposed for the Triangle model and the Two-term Gaussian model.

1. Gradient Profile Transformation Model for profiles approximated using the Triangle Model

To conserve the shape and sum of the gradient magnitudes in a given gradient profile consistent throughout the transformation, there is a need to preserve the area of the triangle equal before and after the transformation.

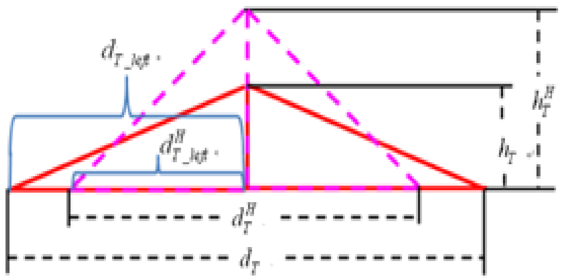


Fig. 4.SOURCE: REFERENCE [1], Transformation of triangle model where its area is conserved.

Thus, to maintain the area and shape of the triangular approximation of the gradient profile, the features of the GPS ratio i.e. 'h' and 'd' are varied, transformed to describe the profile in the target HR grid. The value using which these features are varied is termed as the GPS Enhancement Parameter, denoted by 'α'.This parameter is derived based on the transformation relationship between the gradient profiles of LR image and the up-scaled image.

Thus, the GPS transformation for triangle model is extracted as follows:

$$h_T^H = h * \sqrt{\propto}$$

$$d_T^H = d * \sqrt{(1/\propto)} \qquad (4)$$

Since Triangle model is a linear fitting model, thus the gradient magnitude at every point on the gradient profile can be retrieved using the slope-intercept formulation of the model.

2. Gradient Profile Transformation Model for profiles approximated using the Two-term Gaussian Model

These gradient profiles do not have a regular linear shape, thus the transformation is complicated as compared to that of the Triangle model. To obtain transformation of gradient profiles, the spatial scattering and the gradient magnitude of the peak pixel approximated using the Gaussian model are varied based on the enhancement parameter or the up-scaling ratio, conserving the profile shape.

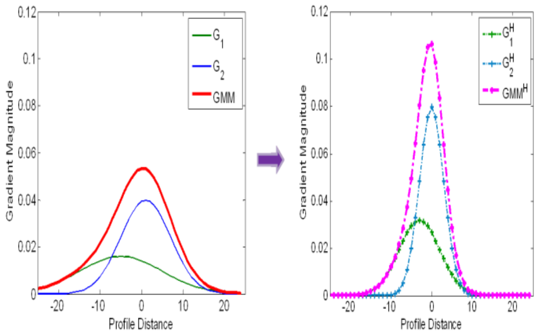


Fig. 5. SOURCE: REFERENCE [1], Gradient transformation based on the Gaussian mixture model.

The GPS transformation for the profiles approximated using the Gaussian Mixture model is formulated as:

$a_1^H = a_1 \quad , \quad a_2^H = a_2$

$b_1^H = \lambda b_1 \quad , \quad b_2^H = \lambda b_2$

$c_1^H = \lambda c_1 \quad , \quad c_2^H = \lambda c_2$

$$\lambda = \sqrt{\left(\frac{1}{\alpha}\right)} \quad (5)$$

From these transformed features of the two models, we deduce the sub-pixel information contents to obtain super-resolution. The GPS ratio for a provided gradient profile is transformed as:

$$\eta^H = \frac{h^H}{d^H} = \frac{h}{d\lambda^2} = \frac{\eta}{\lambda^2} = \alpha\eta \qquad (6)$$

The transformed GPS is then added as a prior image to the High Resolution Image Reconstruction model. The incorporation of prior image minimizes the sum of errors that occur during reconstruction in the gradient domain as well as in the image spatial domain.

E. THE GENERALIZED ALGORITHM

The SR methodology developed in the paper can be realized as the formulation of following framework steps:

1. Compute GPS ratio for a given gradient profile using the Triangle model or the Two-term Gaussian model.

2. The GPS ratio transformation is studied for obtaining a required up-scaling ratio.

3. The GPS transformation relationship is estimated.

4. Based on the computed transformation relation, the gradient profiles of the LR grid are transformed for generation of target gradient profiles in the HR grid.

5. The HR Image reconstruction model is formulated based on the transformed gradient profiles to finally obtain a HR image.

IV. RESULTS AND DISCUSSIONS

Researchers are satisfied by the simplicity and computational efficiency of spatial domain analysis. Thus, recently in the research domain, the processing domain is chosen to be spatial. The GPS SR is based on spatial enlargement as well as preserving the profile shape consistent throughout the transformation. By implementing the two gradient description models for the gradient profiles of the edge pixels, we obtain adequate information about its sharpness and contrast. The type gradient profile obtained for a sharp and smooth edge is referenced in Fig.1. The fitting results of the two GPS models is represented in Fig.2 and Fig.3.The fitting parameters associated with both the models are extracted and transformed based on the upscale required ratio.

Fig.4 and Fig.5 depict the transformation of gradient profile shapes, required to obtain gradient profiles in the target field.

V. CONCLUSION

In this paper, a Single Image SR technique is proposed which focuses on augmentation of spatial resolution of the image as well as edge sharpness and contrast enhancement. The two prominent models presented through the paper i.e. the Triangle Model and the two-term Gaussian model are flexible and thus provide optimized approximation of the gradient profiles of the decimated image. These gradient profiles are then converted to ones resembling gradient profiles in the target field. Finally, these are then added as image priors to the HR image reconstruction model. The technique efficiently conserves the quantitative information in the form of gradient magnitude and the quality in the form of shape of the gradient profile is preserved.The technique uses the Least squares algorithm to minimize the errors produced during fitting. The proposed approach is efficient and can faithfully extract High resolution details from a provided LR image. In the future, as the applications would change, the SR algorithms also have a scope of advancements.

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