LOCAL AND GLOBAL FEATURE LEARNING FOR BLIND QUALITY EVALUATION OF SCREEN CONTENT AND NATURAL SCENE IMAGES

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ABSTRACT
The blind quality evaluation of screen content images (SCIs) and natural scene images (NSIs) has become an important, yet very challenging issue. In this paper, we present an effective blind quality evaluation technique for SCIs and NSIs based on a dictionary of learned local and global quality features. First, a local dictionary is constructed using local normalized image patches and conventional K-means clustering. With this local dictionary, the learned local quality features can be obtained using a locality-constrained linear coding with max pooling. To extract the learned global quality features, the histogram representations of binary patterns are concatenated to form a global dictionary. The collaborative representation algorithm is used to efficiently code the learned global quality features of the distorted images using this dictionary. Finally, kernel-based support vector regression is used to integrate these features into an overall quality score. Extensive experiments involving the proposed evaluation technique demonstrate that in comparison with most relevant metrics, the proposed blind metric yields significantly higher consistency in line with subjective fidelity ratings. We propose structure consistent patch matching to take the distribution of source and target patch differences into account. Fast Fourier transform is adapted for full image searching to achieve better and faster matching results. Experimental results are given to demonstrate the improvements made by our proposed method.

I INTRODUCTION

The Image resolution enhancement is a usable preprocess for many satellite image processing applications, such as vehicle recognition, bridge recognition, and building recognition to name a few. Image resolution enhancement techniques can be categorized into two major classes according to the domain they are applied in: 1) image-domain; and 2) transform-domain. The techniques in image-domain use the statistical and geometric data directly extracted from the input image itself [1], [2],while transform-domain techniques use transformations such as decimated discrete wavelet transform to achieve the image resolution enhancement [3]–[6].

The decimated discrete wavelet transform (DWT) has been widely used for performing image resolution enhancement [3]–[5]. A common assumption of DWT-based image resolution enhancement is that the low-resolution (LR) image is the low-pass filtered sub band of the wavelet-transformed higher solution (HR) image. This type of approach requires the estimation of wavelet coefficients in sub bands containing high-pass spatial frequency information in order to estimate the HR image from the LR image.

In order to estimate the high-pass spatial frequency information, many different approaches have been introduced. In [3], [4], only the high-pass coefficients with significant magnitudes are estimated as the evolution of the wavelet coefficients among the scales. The performance is mainly affected from the fact that the signs of estimated coefficients are copied directly from parent coefficients without any attempt being made to estimate the actual signs. This is contradictory to the fact that there is very little correlation between the signs of the parent coefficients and their descendants. As a result, the signs of the coefficients estimated using extreme evolution techniques cannot be relied upon. Hidden Markov tree (HMT) based method in [5] models the unknown wavelet coefficients as belonging to mixed Gaussian distributions which are symmetrical about the zero mean.

HMT models are used to determine the most probable state for the coefficients to be estimated. The performance also suffers mainly from the sign changes between the scales. The decimated DWT is not shift-invariant and, as a result, suppression of wavelet coefficients introduces artifacts into the image which manifests as ringing in the neighborhood of discontinuities [6]. In order to combat this drawback in DWT-perceptual and objective quality of the resolution enhanced images by their method compare favorably with recent methods [3], [5] in the field.

Dual-tree complex wavelet transform (DT-CWT) is introduced to alleviate the drawbacks caused by the decimated DWT [7]. It is shift invariant and has improved directional resolution when compared with that of the decimated DWT. Such features make it suitable for image resolution enhancement. In this letter, a complex wavelet-domain image resolution enhancement algorithm based on the estimation of wavelet coefficients at high resolution scales is proposed. The initial estimate of the HR image is constructed by applying cycle spinning methodology [6] in DT-CWT domain. It is then decomposed using the one-level DT-CWT to create a set of high-pass coefficients at the same spatial resolution of the LR image. The high-pass coefficients together with the LR image are used to reconstruct the HR image using inverse DT-CWT.

The letter is organized as follows. Section II gives a brief review of the DTCWT. Section III describes the proposed DT-CWT domain satellite image resolution enhancement algorithm.

Section IV provides some experimental results of the proposed approach and comparisons with the approaches in [1], [2], [4], and [6]. Section V concludes the letter.

Resolution has been frequently referred as an important property of an image. Images are being processed in order to obtain super enhanced resolution. One of the commonly used techniques for image resolution enhancement is Interpolation has been widely used in many image processing applications. Interpolation in image processing is a method to increase the number of pixels in a digital image. Traditionally there are three techniques for image interpolation namely Linear, Nearest Neighbor and cubic. Nearest Neighbor result in significant ―Jaggy‖ edge distortion. The Bilinear Interpolation result in smoother edges but somewhat blurred appearance overall. Bucolic Interpolation look's best with smooth edges and much less blurring than the bilinear result .By applying the 1-D discrete wavelet transform (DWT) along the rows of the image first, and then along the columns to produce 2-D decomposition of image.DWT produce four sub bands low-low (LL), low high (LH), high-low (HL) and high-high (HH).By using these four sub bands we can regenerate original image.

Image Enhancement Techniques

Denote a two-dimensional digital image of gray-level intensities by I. The image I is ordinarily represented in software accessible form as an M × N matrix containing indexed elements I(i, j), where 0 i M - 1, 0 j N - 1. The elements I(i, j) represent samples of the image intensities, usually called pixels (picture elements). For simplicity, we assume that these come from a finite integer-valued range. This is not unreasonable, since a finite word length must be used to represent the intensities. Typically, the pixels represent optical intensity, but they may also represent other attributes of sensed radiation, such as radar, electron micrographs, x rays, or thermal imagery.

Point Operations

Often, images obtained via photography, digital photography, flatbed scanning, or other sensors can be of low quality due to a poor image contrast or, more generally, from a poor usage of the available range of possible gray levels. The images may suffer from overexposure or from underexposure, as in the mandrill image in Fig. 1(a). In performing image enhancement, we seek to compute J, an enhanced version of I. The most basic methods of image enhancement involve point operations, where each pixel in the enhanced image is computed as a one-to-one function of the corresponding pixel in the original image: J (i, j) = f [I (i, j)]. The most common point operation is the linear contrast stretching operation, which seeks to maximally utilize the available gray-scale range. If a is the minimum intensity value in image I and b is the maximum, the point operation for linear contrast stretching is defined by

$$J(i, j) = \frac{K-1}{b-a}[I(i, j) - a] \qquad (1)$$

Assuming that the pixel intensities are bounded by 0 I (i, j) K - 1, where K is the number of available pixel intensities. The result image J then has maximum gray level K - 1 and minimum gray level 0, with the other gray levels being distributed in-between according to Eq. (1). Figure 1(b) shows the result of linear contrast stretching on Fig. 1(a).

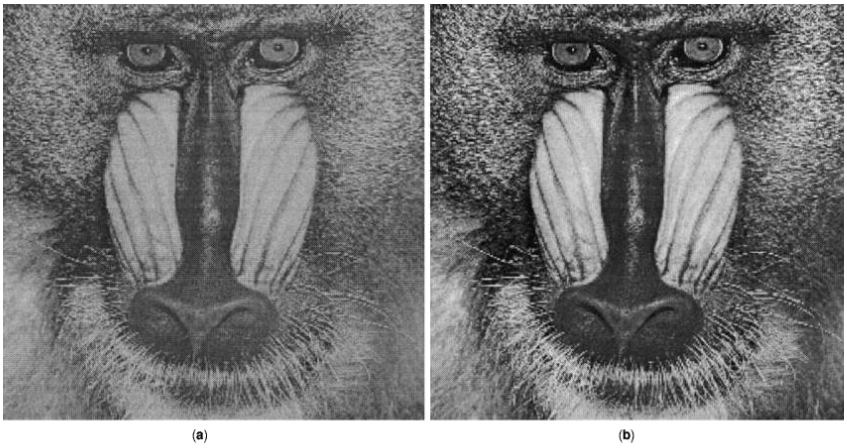


Figure 1. (a) Original Mandrill image (low contrast). (b) Mandrill enhanced by linear contrast stretching. (c) Mandrill

Several point operations utilize the image histogram, which is a graph of the frequency of occurrence of each gray level in I. The histogram value HI(k) equals n only if the image I contains exactly n pixels with gray level k.

Qualitatively, an image that has a flat or well-distributed histogram may often strike an excellent balance between contrast and preservation of detail.

Histogram flattening, also called histogram equalization in Gonzales and Woods (1), may be used to transform an image I into an image J with approximately flat histogram. This transformation can be achieved by assigning.

$$J(i, j) = (K-1)P(i, j) \qquad (2)$$

Where P (i, j) is a sample cumulative probability formed by using the histogram of I:

$$P(i, j) = \frac{1}{MN}\sum_{k=0}^{I(i,j)} H_1(k) \qquad (3)$$

The image in Fig. 1(c) is a histogram-flattened version of Fig. 1(a).

A third point operation, frame averaging, is useful when it is possible to obtain multiple images Gi, i = 1, n, of the same scene, each a version of the ideal image I to which deleterious noise has been unintentionally added:

$$\mathbf{G}_i = \mathbf{I} + \mathbf{N}_i \qquad (4)$$

where each noise image Ni is an M × N matrix of discrete random variables with zero mean and variance 2 . The noise may arise as electrical noise, noise in a communications channel, thermal noise, or noise in the sensed radiation. If the noise images are not mutually correlated, then averaging the n frames together will form an effective estimate Î of the uncorrupted image I, which will have a variance of only 2 /n:

$$\hat{I}(i,j) = \frac{1}{n}\sum_{i=1}^{n} G_i(i,j) \qquad (5)$$

This technique is only useful, of course, when multiple frames are available of the same scene, when the information content between frames remains unchanged (disallowing, for example, motion between frames), and when the noise content does change between frames. Examples arise quite often, however.

For example, frame averaging is often used to enhance synthetic aperture radar images, confocal microscope images, and electron micrographs.

II LITERATURE SURVAY

S. SINDHUMOL; A. KUMAR; K. BALAKRISHNAN: A NEW ENHANCEMENT APPROACH FOR ENHANCING IMAGE OF DIGITAL CAMERAS BY CHANGING THE CONTRAST

There are four well-known traditional interpolation techniques namely nearest neighbor, linear, and Lanczos. In [4] using bilinear, bicubic method the PSNR values for Lena's image are 26.34 and 26.86. W. Knox. Carey, Daniel. B. Chuang, and S. S. Hemami in [5] presented the regularity-preserving interpolation technique for image resolution enhancement synthesizes a new wavelet sub band based on the known wavelet transform coefficients decay. Which gives PSNR (db) value for Lena's Image as 31.7 [5]. Xin. Li and Michael. T. Orchard in [6] presented a hybrid approach produced by combining bilinear interpolation and covariance-based adaptive interpolation called New Edge-Directed Interpolation Which gives PSNR(db) value for Lena's Image as 28.81 [4]. Alptekin. Temizel and Theo. Vlachos in [7] presented technique named "Wavelet domain image resolution enhancement using cycle-spinning and edge modeling ", which improves PSNR (db) values for Lena's image up to 29.27 [4]. Hasan. Demirel and Gholamreza. Anbarjafari in [8] presented an approach DT-CWT based image resolution enhancement which gives PSNR (db) value for Lena's Image as 33.74 [4]. Gholamreza. Anbarjafari and Hasan. Demirel in [9] presented a method named "Image super resolution based on interpolation of wavelet domain high frequency sub bands and the spatial domain input image", which gives PSNR(db) value for Lena's image up to 34.79 [4]. Hasan. Demirel and Gholamreza. Anbarjafari in [4] presented new method named "Image Resolution Enhancement by Using Discrete and Stationary Wavelet Decomposition", which give PSNR(db) value for Lena's image as 34.82 [4].

B. V. PATEL; A. V. DEORANKAR; B. B. MESHRAM: CONTENT BASED VIDEO RETRIEVAL USING ENTROPY, EDGE DETECTION, and BLACK AND WHITE COLOR FEATURES

In this paper we propose integration of entropy and black and white points on edge, features of video key frames for developing proposed video retrieval systems. First, video feature database is created using entropy feature extracted from key video frames of video database. Same feature is extracted from video frame query. We then extract the edge and black and white points on edge from database frames and query frame. Finally similarity measure is applied to retrieve the best matching frames and corresponding videos are presented as output. The experimental results show that feature integration is effective. In this paper we use Content Based Video Retrieval (CBVR), system works more effectively as these deals with content of video rather than video metadata. Proposed Content Based Video Retrieval Systems works on two modules i.e.

- Creation of feature database.
- Retrieval using query feature extraction with similarity measures.

First module of database creation includes key frames extraction from video dataset. For every key frame, GLC is constructed and entropy is calculated. Entropy value for every key frame is stored with the metadata information of frame. This data base is then sorted for faster retrieval process. Second module receives query video frame input from the user. Entropy is calculated with the help of GCL matrix. Black and white points are computed on the edge, detected using Prewitt edge detection approach and compared between query frame and every key frame of the database. We have presented novel approach for video retrieval. Proposed method can be used for retrieval of criminal information, learning, news video browsing, and digital multimedia library retrieval and defense applications. This approach can further be enhanced by integrating content features like frequency, histogram, etc with data mining techniques.

DISADVANTAGE

- Video processing always is performed on frames which are basic block of video.
- Group of frames captured together is called shot.
- Storing and processing theses individual frames are memory and computational. expensive.

III THEORETICAL BACKGROUND

3.1 PROBLEM IDENTIFICATION

- Image in painting is an ill-pose problem since there is no well- defined unique solution.
- The pixels in the unknown regions are assumed to have same statistical properties or geometrical structures with some pixels in the known regions, based on which they are estimated.
- There are mainly two categories of image in- painting methods.
- The first category is the diffusion-based in painting, where parametric models are established by partial differential equations to propagate the local structures from known regions to unknown regions.
- It was first introduced by Bertalmio et al. and realized as the Bertalmio Sapiro Caselles Ballester method. This method simulates the repairing process of professional artists by

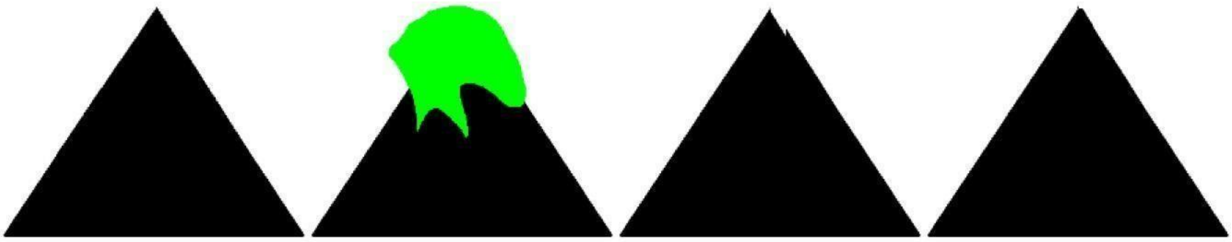
propagating image information alongthe isophote.

DISADVANTAGES

- Image in painting has been conventionally defined as the process of reconstructing lost or detoriated parts of images.
- The entire workflow involves an input image an image which has some defect to it, and an output image that is free of that defect.
- Usually the defect is of such nature that it leads to absence of some part of the original scene (which was captured) in the current version.
- The output is an image that reconstructs the part that was lost.
- However, this isn’t where in painting ends. Restoration is just an application of it, just as object removal is. In painting is also used to remove large objects from the image. 34 Here the challenge is to fill in the hole that is left behind in a visually plausible way.

3.2 PROBLEM SOLVING

- We propose an exemplar-based image in painting using structure consistent patch matching method, which has the following merits.
- First, a space varying updating strategy for the confidence term and a matching confidence term are proposed to reduce the fast dropping effect and improve the priority estimation, which is critical to the final in painting results.
- Second, we propose a structure consistent patch matching to take the distribution of patch differences into account. In the last, fast Fourier transform (FFT) is adapted for full image searching to achieve better and faster matching results.
- Criminisi method has the advantages of both diffusion-based in painting and texture synthesis.
- It can restore structure and texture information simultaneously and achieves good performance on images with large lost regions and images composed of textures and structures.
- A triangle is simulated to demonstrate the improvement by using the priority function with the proposed space varying updating strategy for the confidence term and the additional matching confidence term.
- The proposed method is compared with the priority function of the Criminisi method.



(a) (b) (c) (d)

(a) The original image

(b) The image with green target region.

(c) The result of the Criminisi method.

(d) The result of the proposed method.

3.3 SYSTEM ARCHITECTURE

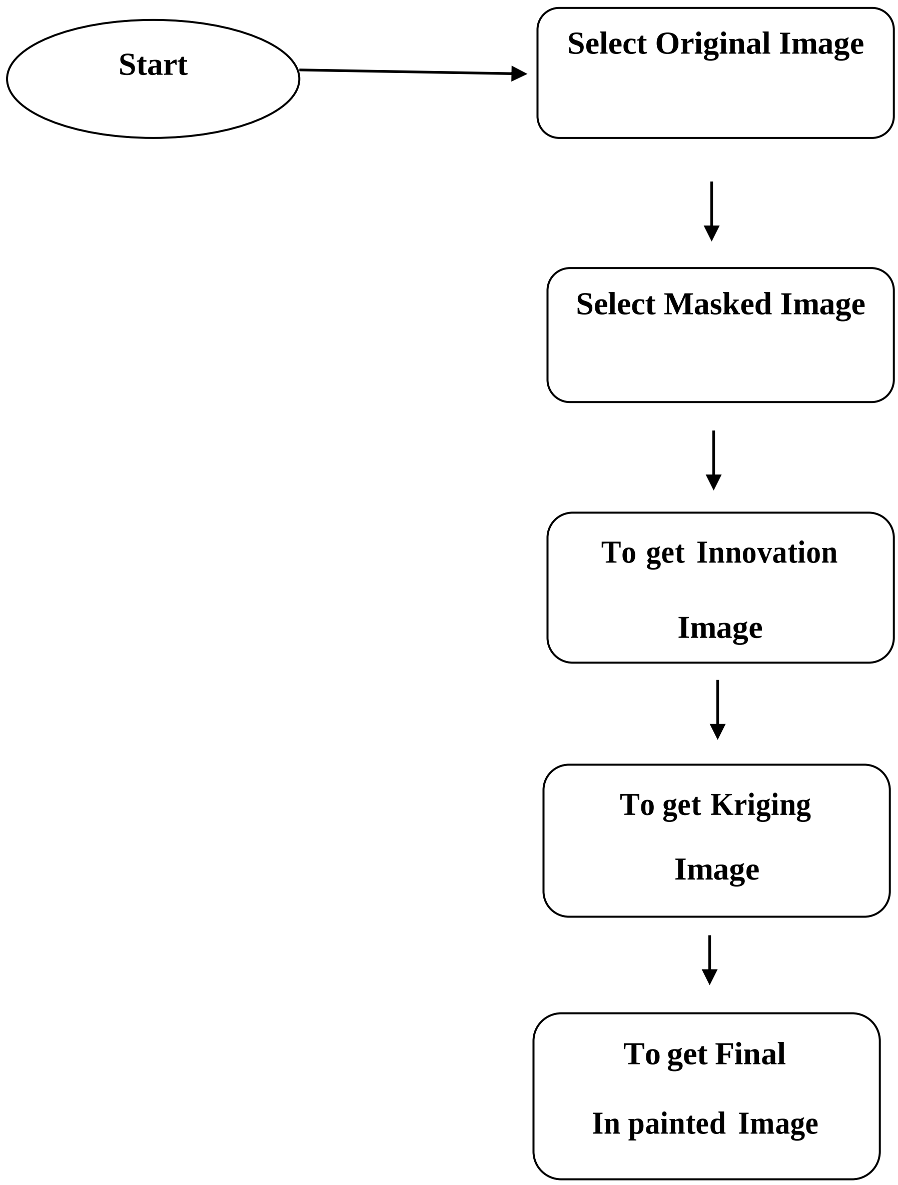


Figure 3.1 Architecture Design

IV SYSTEM IMPLEMETATION

4.1. COMPUTING PATCH PRIORITIES

The proposed algorithm is a best-first filling algorithm that depends entirely on the priority

values that are assigned to each patch on the fill front. The priority computation is biased toward

Removing large object from images. Right: Original Image, Left: The region corresponding to the foreground person has been manually selected and then automatically removed.

Those patches with are the continuation of strong edges and which are surrounded by high-confidence pixels. This has been discussed in detail in the paper. Henceforth, the patch on the fill front with highest priority will be referred to as, yˆ p.

4.2. PROPAGATING TEXTURE AND STRUCTURE INFORMATION

The patch with the highest priority, yˆ p, is filled with the data extracted from the source region, F. Instead propagating texture using diffusion, which inevitably leads to image smoothing, the image texture is propagated by direct sampling of the source region.

The patch in the source region that is most similar to the target patch is copied as it is. This suffices to achieve the propagation of both structure and texture information from the source F to the target region W.

Henceforth, the patch in the source region that is most similar to the target patch is referred to as Yˆ q. Valid patches Yˆ q must be entirely contained in F.

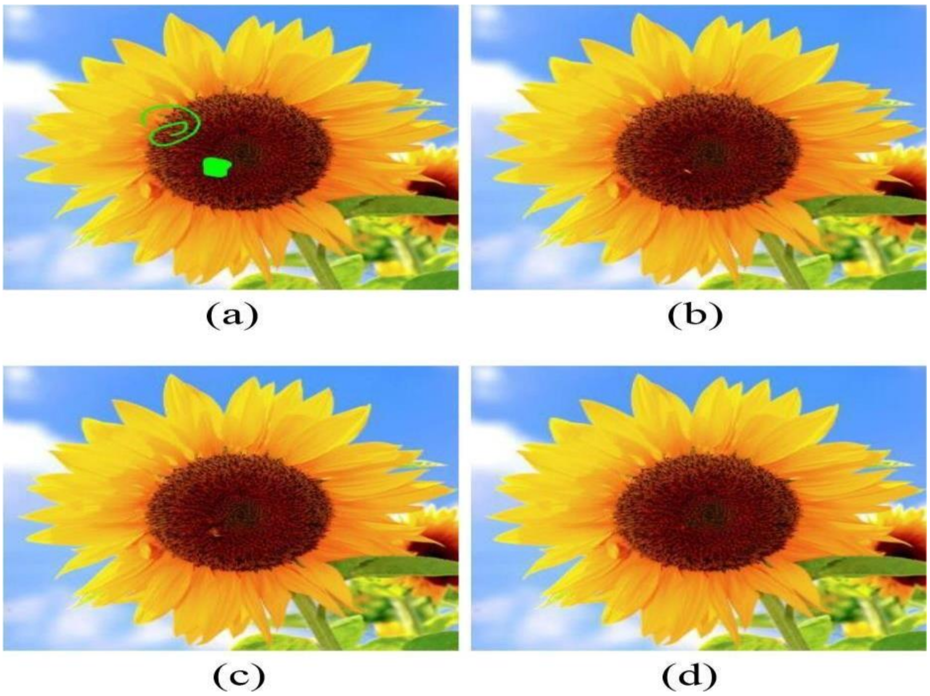
4.3. PRIORITY FUNCTION WITH SPACE VARYING UPDATING STRATEGY AND MATCHING CONFIDENCE

The priority defining the filling order is the key to maintain structure information in exemplar-based image in painting. As presented in Eq. (2), the value of the confidence term drops quickly. The priority advance provided by the structure information through data term soon becomes insignificant when the confidence is very small, which causes loss of structures when in painting structure images. In this paper, we propose an effective updating strategy for the confidence term with two variations to solve the dropping problem.

4.4. STRUCTURE CONSISTENT PATCH MATCHING

The SSD criterion in the Criminisi method only considers the intensity differences between target patch and source patch while neglecting the differences of structure variations within these two patches.

We aim to find a simple but effective criterion to mea- sure the structure consistency between the source patch and target patch, which can also use the information estimated in the SSD calculation so that the computation burden will not be increased. A structure consistent patch matching criterion is thus proposed to evaluate the spatial distribution.



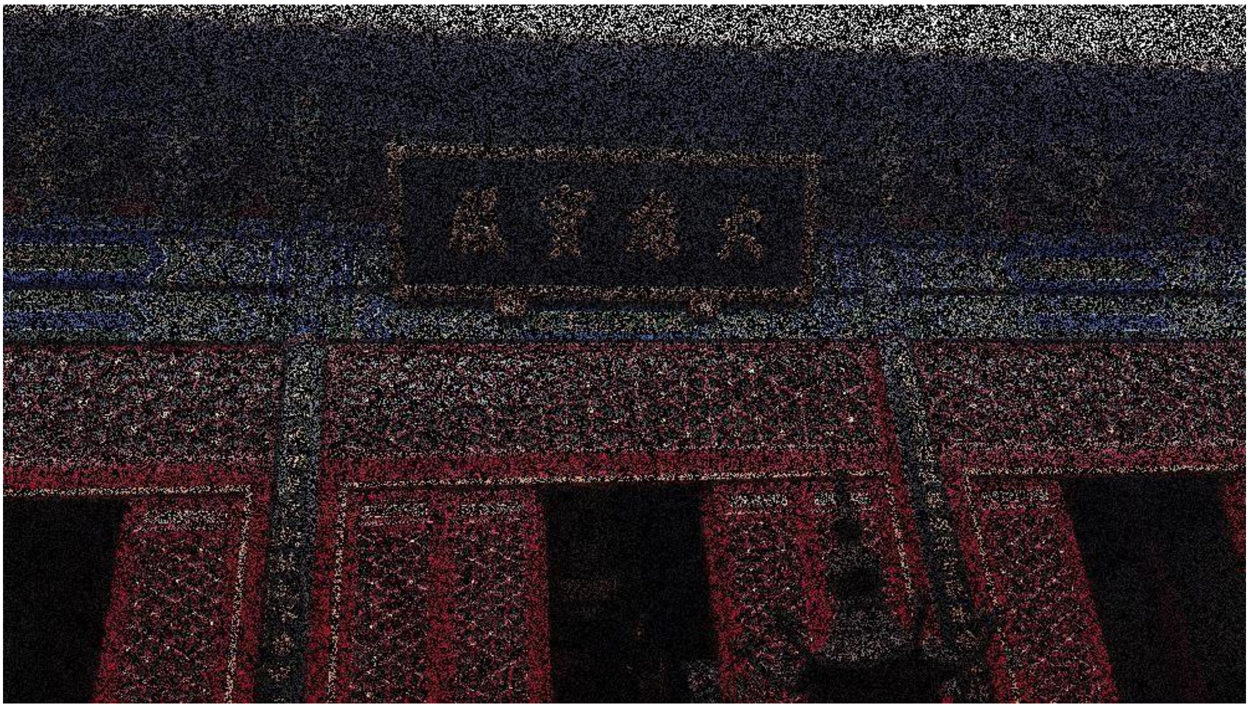
4.5 THE IMPLEMENTATION USING FFT AND THE METHOD OUTLINE

The search of the best matching source patch for the target patch is the most time-consuming part of the exemplar-based

Image in painting, especially when full source region searching is performed for better match. FFT has been used to accelerate the process for SSD calculation. In this section, we will demonstrate how our proposed structure consistent patch matching can be implemented using FFT almost without increasing the computation burden.

V RESULT AND DISCUSSION

To verify the effectiveness of our proposed in painting method, we conduct a series of experiments and compare the results with the Criminals method and the CBD method.



Original input

Delaunay triangulation based interpolation

VI CONCLUSION & FUTURE WORK

6.1 CONCLUSION

A method for image resolution enhancement from a single low-resolution image using the dual-tree complex wavelet is presented. The initial rough estimate of the high-resolution image is decomposed to estimate the complex valued high-pass wavelet coefficients for the input low-resolution image. Estimated complex wavelet coefficients are used together with the input low resolution image to reconstruct the resultant high-resolution image by employing inverse dual-tree complex wavelet transform. Extensive tests and comparisons with the state-of-the-art methods show the superiority of the method presented in this letter. The proposed resolution enhancement method retains both intensity and geometric features of the low-resolution image. Although the method for image enhancement based on Spline is sufficient but in future efficient methods can be develop for image enhancement which can give more accurate result.

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