Single Color Image Super Resolution

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ABSTRACT
The single image super-resolution refers to the process of recovering missing high-resolution details so as to reconstruct a high resolution image(HR) from a single low resolution image (LR). Correspondences between low and high resolution image patches are learned from a database of low and high resolution image pairs, and then applied to a new low-resolution image to recover its most likely high-resolution version. In this paper color image super resolution method is implemented using critically sampled directionlet transform. In this method color image in RGB format is converted to YCbCr format. The luminance component Y alone is super resolved and other two components are interpolated using standard methods. At the end the YCbCr format is converted back to RGB format.

Keywords
Directionlet, anisotropic, super resolution, Colour, RGB

1. INTRODUCTION
Digital image processing has several applications in surveillance, satellite imaging, forensic science, target identification, diagnostics, etc. These applications need High Resolution (HR) images. It is advantageous when images used in the above applications contain more detailed information. The super resolved images not only give the user a pleasing appearance but also offer additional data that is important in many applications. The image acquisition environment condition, resolution of sensors, optical technology used are some of the factors that affect the quality of digital image and captured image will be a low resolution image(LR). Super resolution problem is an inverse problem that refers to the process of reconstructing a HR image than what is afforded by the physical sensor through post processing, making use of one or more LR observations [5]. This techniques include up sampling the image, thereby increasing the maximum spatial frequency and removing degradations that arise during the image capture namely aliasing and blurring. Standard interpolation techniques consider LR image information. They only increase the number of pixels without adding the details and the resulting image is often blurry and contains artefacts. These techniques perform well in smoother regions of the images and tend to blur edges and other sharp details in the images. Here a new learning based single image super resolution method for color images obtained by low resolution cameras..

2. RELATED WORK
In general, there are two types of super resolution techniques: reconstruction-based and learning-based. Frequency domain approach proposed by Tsai in"Multiframe image restoration and registration" [10] was the first work in super resolution. They considered the super resolution problem described above subject to the assumption that the low resolution frames have neither been corrupted by noise nor degraded by a blurring phenomenon. Unlike the reconstruction-based method which requires multiple LR input images, learning based super resolution only one input image (single frame image super resolution) is required. In paper [11], Freeman et al propose an example based super resolution method in which he had developed a Bayesian propagation algorithm using Markov Network. In the paper[9], Pickup et al attempt to shed some light on this problem when the SR algorithms are designed for general natural images (GNIs). In the paper[7] Isabelle presents comparisons of two learning-based super-resolution algorithms as well as standard interpolation methods. The paper [1] presents a color super resolution a procedure based on image colorization and back-projection to perform color assignment guided by the super-resolution luminance channel. The paper [8] presents a color super resolution method based on Convolution neural networks. In the paper [4] authors propose a color super resolution method based on outline a procedure based on image colorization and back-projection to perform color assignment guided by the super-resolution luminance channel The paper [3], Ayan et al present a learning-based method to super-resolve face images using a kernel principal component analysis-based prior model. In the paper titled "Psf recovery from examples for blind super resolution"[6], the authors propose a new learning based approach for super-resolving an image captured at low spatial resolution.

The proposed learning-based method is motivated by the work by Velisavljevic et al [1] , in which directionlets were proved to provide sparse representation of image, like wavelets. This paper is organized as follows. In Section 3, the concepts of Directional transform are presented. This section explains concept of lattice based transform to implement directionlet transform. The color models RGB and YCbCr are explained in Section 4. Experimental results with color test images and the comparison with previous works are presented in Section 5. Finally, conclusions are given in Section 7.

3.DIRECTIONLET TRANSFORM
The directionlet transform (DT) is skewed anisotropic transform and it is an efficient tool for representing images which contains multiple direction oriented and elongated edges. In DT , transforms are applied along random directions and number of transforms are not equal, that is, n1 in one direction and n2 in other direction, where n1 is not necessarily equal to n2. The iteration process is continued in the lower sub-band, as in the standard wavelet transform to obtain multi level transform. Anisotropic transform is represented as AWT(n1,n2)[1]. As already stated the directionlet transform is obtained by applying transform in two random directions, not necessarily along horizontal and vertical directions. For this, the transform can be taken on two random digital lines which causes a problem called directional interaction. That is the concept of digital lines is not enough to provide a systematic rule for sub sampling. To overcome the problem of directional interaction and the concept of integer

lattices is proposed by Velisavljevic et al[1] ..

4.COLOR MODEL

4.1 RGB Color model

In the RGB model which is also called additive model, each color is represented as a combination of primary colors red, green, and blue. The primary colors can be added to produce the secondary colors of light - magenta (red plus blue), cyan (green plus blue), and yellow (red plus green). The number of bits used to represent each pixel in RGB space is called pixel depth.

4.2 YCbCr Color Model

Y is the luminance component and Cb and Cr are the blue difference and red-difference chroma components. It can be noted that the Y image is essentially a grey scale copy of the original image. The principal advantage of the YCbCr model in image processing is decoupling of luminance and color information. The importance of this decoupling is that the luminance component of an image can be processed without affecting its color component.

5. SINGLE IMAGE SUPER RESOLUTION USING CRITICALY SAMPLED DIRECTIONLET TRANSFORM IN COLOR IMAGES

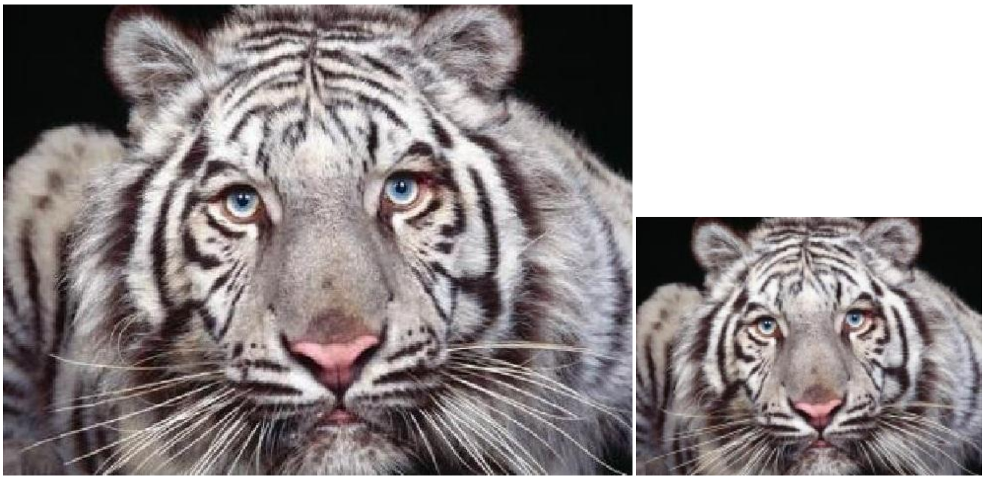
There are different ways to super resolve color images in RGB format. The typical solution involves applying monochromatic SR algorithms to each of the color channels independently. This process can result in better performance than super-resolving only the luminance components, both in terms of SNR values and in visual plausibility. But it is at the expense of three times larger run-time complexity. Humans are more sensitive to the brightness information(luminance) than color information(chrominance components).A new method in which chrominance layers are separated from luminance, and super resolution method is applied only to the luminance channel. The chrominance or color channels, are then up sampled using interpolation methods (eg. bilinear, bicubic) and the final RGB is computed by recombining the new SR luminance image with the interpolated chrominance. Processing the luminance information does not reduce the quality of resultant image, but this method reduces the computation time.

Fig 1: If necessary, the images can be extended both columns

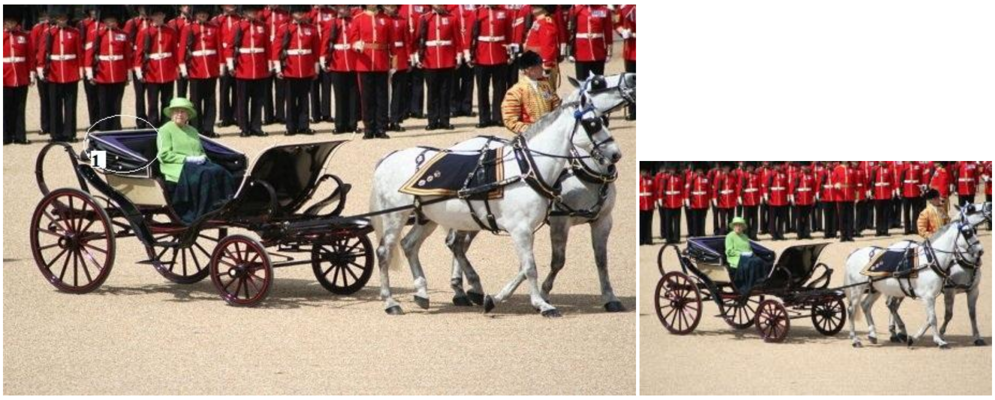
5.1 Color image Super resolution with super resolution on luminance component only.

In this method the RGB color image is converted into YCbCr model and the super resolution is performed only on the luminance Y component. The main advantage of the YCbCr model in image processing is that the luminance and the color information are independent. Thus, the luminance component can be processed without affecting the color contents. The details information in a digital image is mainly present in the image luminance component. Therefore, one can take advantage of the high sensibility of the human visual system to the brightness variation than to the chrominance variation. Consequently,. more computational resources can be allocated to enlarge the brightness values while color components can be enlarged using a simpler approach. The final result is then obtained by combining the super-resolved Y component with the interpolated Cb and Cr components. Finally, the YCbCr model is converted to the RGB model to generate the synthetic image

The new method presented in this paper uses a training set which contains different frequency features of available high resolution images. These features are used to obtain the high resolution version of an image captured using a low resolution camera. The idea used here is to learn the HR representation mapping of an LR edge from the training dataset during up sampling. Directionlet transform is used here to decompose images into different frequency bands. In the training set, information about patches or small blocks of Luminance component of high resolution images and their corresponding low resolution components are stored in terms of the coefficients of directionlet transform. This method uses critically sampled directionlets. To generate a training set, a collection of high resolution images and their low resolution (LR) images are used. LR images are formed by averaging the intensities of non overlapping block of size 2×2 pixels from HR image. The HR and LR images in RGB model are



(a) (b



(c)

Figure 2. (a)(c)Original images(b)(d)Low resolution images

converted to YCbCr model. Directional information of the corresponding luminance components are extracted using directionlet transform. In the case of images, the directional information varies over space. Thus, directionality can be considered as a local feature, defined in a small neighborhood. Therefore, to extract directional variations of an image it has to be analyzed locally.

The following steps are used to obtain HR component of luminance component Y ,

(1) The low and high resolution luminance components are partitioned into small blocks of size 4×4 and 8×8 (with suitable overlapping with four neighboring patches) respectively and patches are contrast normalized by energy of LR patch.

(2) Suitable pair of directions for each LR patch is found out and Directionlet transform coefficients of that patch and its HR patch, along the selected pair of directions, are saved as the training set in five groups according to five pairs of directions.

(3) The luminance component of given LR input image is also partitioned into small blocks and directionlet transform is applied to it, along its selected pair of directions.

(4) Directionlet coefficients of this input patch are compared with those of the LR patches in the training set, using minimum absolute difference criterion.

(5) LR patch with minimum absolute difference is selected and coefficients of the corresponding high frequency bands are used as the missing bands for the unknown HR patch.

(6) Take the inverse directionlet transform to obtain the HR patch .

(7) Repeat the above process for the remaining input patches to obtain the missing Luminance component

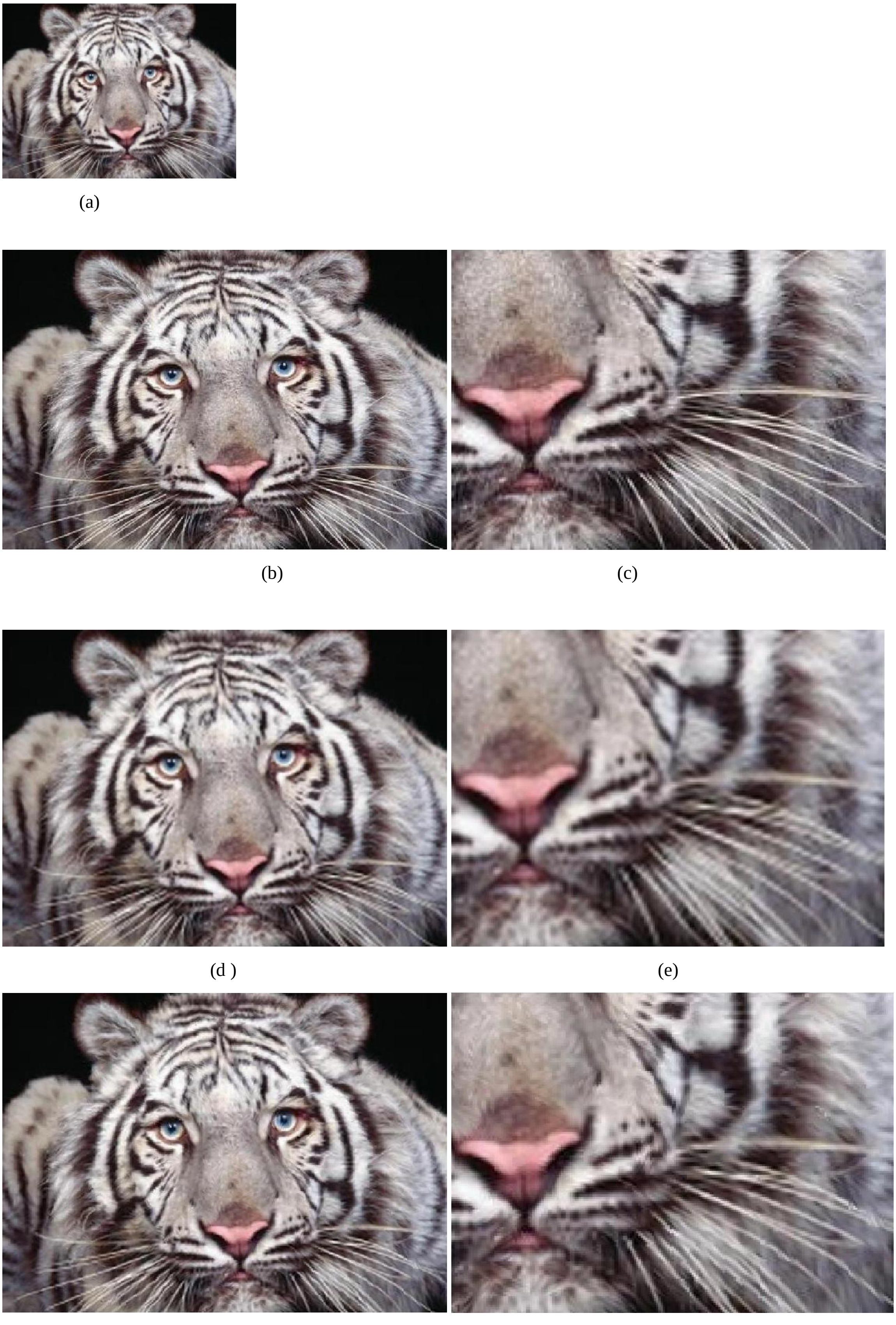


Figure 3. (a)Low resolution image (b)original image(d)cubic spline interpolated image(f)super resolved image using directionlets(c),(e),(g)zoomed portion of the face of (b),(d),(f)respectively

Table 1. SNR values of Super resolved Color images.

Method	SNR in DB			
	Girl1	Girl2	Tiger	Line
Cubic spline	40.3625	21.1581	24.6590	13.7509
Directionlet method	43.5548	37.3297	29.2922	20.1414

5.1.1. Implementation

High resolution color images are obtained from the internet and are used to form training set. The images are obtained from canon digital picture [2]. One of the training set image is shown in Figure1. It is of size 333 x 500 and in tiff format. Some of high and corresponding low resolution images are shown in Figure 2.

In Figures 3(c) and (e) show cubic spline interpolated image and super resolved image of low resolution image in Figure 2(b). Low resolution image is of size 196x292 and it is super resolved to the size of 392x584. The block effect in the marked area of cubic spline interpolated image is almost removed in the super resolved image.

6. RESULTS

SNR values are calculated and shown in table 1. Table shows that the super resolved image girl1 has got SNR of 43.5548dB while cubic spline interpolated image has SNR value 40.3625dB. . The low resolution image used is shown in 2(b). It is of size 200×150. Figures 3(b), (d), (f) show original image, cubic spline interpolated image and super resolved image (400 × 300). Figures 3(c),(e),(g) show zoomed portions of (b), (d), (f) respectively. The ringing effects present in the mustache of tiger in cubic spline interpolated image are almost removed in directionlet based method.

7.CONCLUSION

In this paper directionlet based super resolution method for color images is proposed . In this method, the low resolution image in RGB format is converted to YCbCr format and super resolution method is applied to the luminance component, Y alone. The other chromatic components Cb, Cr are interpolated using cubic spline method. The resulting YCbCr format is converted to RGB format to obtain the high resolution image. It is seen that directionlet based super resolved method outperforms the standard interpolation methods. In the future work, computation and time reducing methods can be included so that the method can be used in real time applications.

8. REFERENCES

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