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Directional variation adaptive image resolution enhancement

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ABSTRACT

The goal of image interpolation is to produce a high-resolution image from its low-resolution counterpart. It has significant applications in video sensor network, where the resolution of images usually needs to be enhanced at the end user due to the limited transmission bandwidth. The key challenge of image interpolation is to preserve the edge structure of the image. In this paper, a new image interpolation approach is proposed to adaptively adjust the interpolation according to the directional variations of images. More specifically, at each pixel position to be interpolated, its neighboring pixels are projected onto 1D direction according to a number of proposed patterns. Then the direction, of which the variation is smallest, is chosen as the direction to perform image interpolation. Experimental results are provided to show that the proposed approach outperforms several conventional edge-directed image interpolation algorithms.

1. Introduction

Video sensor network exploits a set of spatially distributed video sensors, each of which is equipped with a video camera, to capture and process visual information about a scene. It has been applied for a wide range of applications, such as video surveillance and security monitoring [1–3]. The images received usually yield fairly low resolution due to limited storage and transmission bandwidth. Therefore, image interpolation is a required image processing task, which has a capability to produce a high-resolution image from its low-resolution counterpart, for many applications, such as high definition TV display [4–7]. For example, the video captured using a built-in camera of handphone is often stored at low resolutions (e.g. 352×288 pixels). If it needs to be displayed at TV monitor to watch at full screen with a resolution of 1024×768, it requires that image be interpolated to the higher resolution.

Traditional linear polynomial interpolation methods, such as bilinear and bi-cubic interpolations [8], impose continuity constraints on the image. They have low computational complexity, whereas they produce artifacts and blurring in edge regions of the image. It has recently been recognized that improved image quality can be achieved by taking the edge information into account [9–13], where interpolation schemes are adjusted according to local pixel intensity properties so that smoothing is not performed across an edge. However, edges in natural images appear as spatially blurred or noisy edges, it is difficult to explicitly specify the characteristics of edges, such as exact positions and directions, which makes explicit detection of natural edges difficult.

The other edge-adaptive image interpolation aims to perform implicit edge-directed interpolation. Li and Orchard [14] proposed to estimate local covariance coefficients from a low-resolution image and used them to adapt interpolation based on the geometric duality between low-resolution and high-resolution covariances. Hwang and Lee [15] proposed an adaptive interpolation method by applying weights that are inverse to the local gradient information used in bi-linear and bi-cubic interpolations. Zhang and Wu [16] proposed to perform interpolation on two directions and adaptively fuse their results to be single image. Li and Nguyen [17] proposed to measure the continuity strength in multiple directions, where large values indicate strong continuities (along edge directions) while small values indicate weak continuities (across edge directions).

There is another type of image interpolation methods [18–20], which assume that the observed low-resolution image is the low-pass-filtered subband of the wavelet-transformed unknown high-resolution image. They need to estimate wavelet coefficients in subbands containing high-pass spatial frequency information in order to estimate the high-resolution image.

The key challenge of edge-adaptive image interpolation is to determine the edge indicator so that the interpolation needs to be adaptively adjusted according to the local edge properties. In this paper, a new approach is proposed to use directional variations to measure the statistical properties of pixel intensity variations in a local image window. The relative continuity strengths of all directions are used to indicate edge direction, which can be summarized as smaller variation along edge directions and large variation across edge directions. Then the direction with smallest variation will be selected to perform interpolation.

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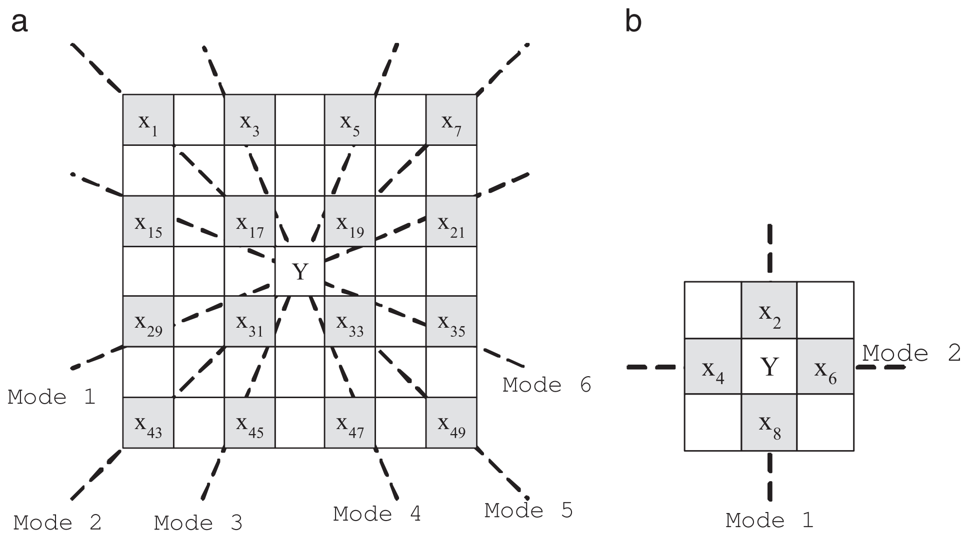

Fig. 1. (a). The neighboring structure used in interpolating pixels at the diagonal direction. (b). The neighboring structure used in interpolating pixels at the horizontal and vertical directions.

Table 1
Various patterns to interpolate pixels in the diagonal direction.

	Projected data	Pixels used for interpolation
Mode 1	x_1,x_3,x_5,x_7,x_{15},x_{17},x_{19},x_{21},x_{29},x_{31},x_{33},x_{35},x_{43},x_{45},x_{47},x_{49}	x_{29},x_{31},x_{19},x_{21}
Mode 2	x_1,x_{15},x_{29},x_3,x_{43},x_{17},x_{31},x_5,x_{45},x_{19},x_{33},x_7,x_{47},x_{21},x_{35},x_{49}	x_7,x_{19},x_{31},x_{43}
Mode 3	x_1,x_{15},x_{29},x_3,x_{43},x_{17},x_{31},x_5,x_{45},x_{19},x_{33},x_7,x_{47},x_{21},x_{35},x_{49}	x_5,x_{19},x_{31},x_{45}
Mode 4	x_7,x_{21},x_{35},x_5,x_{49},x_{19},x_{33},x_3,x_{47},x_{17},x_{31},x_1,x_{45},x_{15},x_{29},x_{43}	x_3,x_{17},x_{33},x_{47}
Mode 5	x_7,x_5,x_{21},x_3,x_{19},x_{35},x_1,x_{17},x_{33},x_{49},x_{15},x_{31},x_{47},x_{29},x_{45},x_{43}	x_1,x_{17},x_{33},x_{49}
Mode 6	x_7,x_5,x_3,x_{21},x_1,x_{19},x_{17},x_{15},x_{35},x_{33},x_{31},x_{49},x_{29},x_{47},x_{45},x_{43}	x_{15},x_{17},x_{33},x_{35}

The rest of this paper is organized as follows. Section 2 presents how the edge direction can be determined by the proposed directional variation criterion, followed by an example to demonstrate the idea of the proposed approach. This criterion is further exploited to propose a variation-adaptive image interpolation approach. Experimental results are provided in Section 3. Finally, Section 4 concludes this paper.

2. Proposed variation-based image interpolation approach

Conventional edge detectors divide an image window in half and compare two sides to see if they are “different”. Then the edge direction is determined as the one with smaller difference. Most edge detectors calculate an average value for each side and then compute the Euclidean distance. However, this way is sensitive to noise and illumination change in the image. In contrast to the above way, the proposed approach converts the measuring edge of a 2D image into a measuring of 1D data, by projecting the 2D image onto pre-defined patterns. If the direction is the same as the edge direction, the variation of the projected 1D data will be small. Otherwise, if the direction is orthogonal to the edge direction, then the variation of the projected 1D data will be large.

Table 2
Various patterns to interpolate pixels in the horizontal and vertical directions.

	Projected data	Pixels used for interpolation
Mode 1	x_4,x_2,x_8,x_6	x_2,x_8
Mode 2	x_2,x_4,x_6,x_8	x_4,x_6

Table 3
The PSNR (in dB) performance comparison.

Test image	Spline interpolation	Ref. [14]	Ref. [16]	Ref. [15]	Ref. [21]	Ref. [22]	Proposed approach
Bike	17.41	20.97	20.26	20.33	21.12	22.33	22.71
Leaf	18.41	21.54	21.26	20.16	21.90	21.94	22.31

For the understanding of the key idea mentioned above, a 4×4 windowed sub-image is used as an example for illustrating the proposed idea as follows:

$$\begin{pmatrix} 70 & 173 & 255 & 244 \\ 166 & 73 & 234 & 248 \\ 246 & 88 & 140 & 255 \\ 254 & 195 & 64 & 215 \end{pmatrix} \tag{1}$$

To identify the edge direction of this sub-image, it can be projected into two orthogonal directions: 45′ and 135′. First, if they are projected on the direction 45′, the resulted 1D data is

$$[70, 173, 166, 255, 73, 246, 244, 234, 86, 254, 248, 140, 195, 255, 64, 215]. \tag{2}$$

And the variation of the projected 1D data, which is measured in terms of the summation of absolute difference, is 1439. Second, if they are projected on the direction 135′, the resulted 1D data is

$$[254, 246, 195, 166, 88, 64, 70, 73, 140, 215, 173, 234, 255, 255, 248, 244]. \tag{3}$$

And the variation of the projected 1D data, which is measured in terms of the summation of absolute difference, is 476. Comparing the above two variations of two directions (i.e., 1439 and 476), one

Table 4
The *feature similarity index*[23] performance comparison.

Test image	Spline interpolation	Ref. [14]	Ref. [16]	Ref. [15]	Ref. [21]	Ref. [22]	Proposed approach
Bike	0.7756	0.8770	0.8569	0.8648	0.8766	0.8860	0.9073
Leaf	0.8496	0.9092	0.9126	0.9091	0.9277	0.9046	0.9281