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Improved image magnification algorithm based on Otsu thresholding ☆

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ABSTRACT

An improved image magnification algorithm for gray and color images is presented in this paper to meet the challenge of preserving high-frequency components of an image, including both image edges and texture structures. In the proposed algorithm, a new edge detection method that uses the well-known Otsu automatic optimum thresholding is proposed to distinguish strong edge pixels. The parameters of the original directional cubic convolution interpolation algorithm, which were selected based on training, were eliminated. As a result, our algorithm achieves more accurate edge detection, better interpolation results, and less computational complexity. Simulation results demonstrate that the improved algorithm can reconstruct the magnified image, preserve edges and textures simultaneously, and reduce common interpolation artifacts. Furthermore, it generates higher visual quality of the magnified images and achieves higher peak signal-to-noise ratio, structural similarity, and feature similarity compared with other state-of-the-art methods.

1. Introduction

Image magnification, which is known as producing high-resolution (HR) images from their low-resolution (LR) counterparts, is highly in demand nowadays and has attracted increasing attention in the research community because of its wide applications in consumer electronics, remote sensing, medical imaging, advertising and printing, and many others. Interpolation is commonly employed in image magnification to estimate unknown pixel values from known pixel values [1]. Many interpolation methods, including adaptive and non-adaptive methods, have been proposed in the last several decades. Classical non-adaptive methods, such as linear and cubic convolution methods [2] are preferable because of their computational simplicity, however, these methods are unable to adapt with varying local structures of a LR image, which causes undesirable artifacts such as blurring, blocking, and ringing around edges [3]. Several adaptive interpolation methods [2,4–15], including edge-directed methods, have been proposed to address the problems of the aforementioned algorithms and to improve the perceptual quality of the interpolated images. Edge-directed methods, which aim for interpolation along edges and not across them, can be classified into two main types: explicit [2,7,10,13,15,16] and implicit [4,6,9,12,14]. Explicit methods perform interpolation along explicitly estimated edge orientations, whereas implicit methods utilize edge characteristics such as orientation and energy via parametric functions [12].

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Li and Orchad [4] proposed a technique to estimate the orientation of edges implicitly by exploiting their geometric duality to estimate the covariance of the HR image from the local covariance of the LR image. Their method guarantees appealing visual quality and smoothened long-edge structures. However, it fails to preserve textures as well as produces some artifacts along edges. Zhang and Wu [6] presented a directional filtering and data fusion technique that interpolates the missing pixel in two orthogonal directions and fuses the results by using linear minimum mean square error estimation, while Giachetti and Asuni [10] proposed an iterative curvature-based interpolation method (ICBI) that interpolates the pixels locally along the direction with a lower second-order derivative value and exploits iterative refinement to remove artifacts and preserve edges and details. However, although ICBI can produce an image with a natural appearance, the final image exhibits ringing artifacts around edges and shows discontinuities in ridges. In addition, ICBI requires high computational cost.

In [8], Getreuer proposed an edge-adaptive image interpolation method. In the method, the local orientation of the image contours is detected by measuring the total variation over a contour stencil. Small total variation along a contour stencil candidate curve indicates approximate smoothness along that curve and thus the stencil is a good approximation to the contour. The method is computationally efficient and shows ability to interpolate edge structures but shows less ability to interpolate texture structures.

Jurio et al. [11] proposed a simple image magnification algorithm based on intervals. In this algorithm, a block expanding approach in which a new block is constructed for every LR image pixel is employed. Each block in the HR image is obtained by a weighted aggregation of the intensities of the pixels in the neighborhood of each pixel in the LR image by making use of the interval information and a linear operator. The interval is constructed from a LR pixel and its neighborhood where the length of the interval is used as a measure of the variation of intensities in the neighborhood. The algorithm is computationally efficient. However, blocking artifacts in edge areas and some pixilation in texture areas are problems of this algorithm.

Recently, Jing and Wu [14] proposed a simple and fast directional inverse distance weighting interpolation method (DIDWI). This method is designed to estimate the intensity distance in the HR image by using the intensity distance in the LR image based on geometric duality between distances in the LR and the HR images along the same direction. However, while DIDWI preserves texture areas, it still suffers from blocking artifacts along strong edges.

Zhou et al. [2] proposed a new directional cubic convolution interpolation (DCCI) algorithm for image zooming. This algorithm explicitly decides the local edge direction based on the ratio of the two orthogonal directional gradients and a preset threshold before interpolating the missing pixel by using cubic convolution interpolation along the detected edge direction. For texture areas, the missing pixel is interpolated by combining the interpolated cubic convolution values and the two orthogonal directional gradients adjusted by a parameter that was determined experimentally. The results, which are heavily dependent on the selection of the two parameters mentioned earlier, show that the DCCI algorithm preserves image edge structures but suffers from directional artifacts in certain texture areas.

In this paper, an improved version of the DCCI algorithm (DCCI_Ostu) is proposed in which a new strong edge detection method is presented. The proposed detection method employs the well-known automatic optimum Otsu thresholding. By eliminating the use of the DCCI parameters, the proposed DCCI_Otsu achieves much more stable results and better magnified image quality in terms of edge and texture preservation with lower computational time. Furthermore, the improved algorithm can magnify color images.

The remainder of this paper is organized as follows: Section 2 presents the related work including the description of the DCCI algorithm and its limitation and Otsu thresholding method. The proposed DCCI_Otsu is presented in Section 3. Section 4 provides the experimental results, including the qualitative and quantitative evaluations. Finally, Section 5 concludes the paper.

2. Related work

In this section, the directional cubic convolution interpolation algorithm and its limitation is first described. Then, a quick review on thresholding is introduced followed by a brief description of Otsu optimum thresholding that will be employed in the proposed DCCI_Otsu.

2.1. DCCI and its limitation

As adopted in various methods [4–9], the DCCI [2] algorithm initially expands the source LR image $X_{(H\times W)}$ with dimension $(H \times W)$ into an HR image $Y_{(2H\text{-}1\times 2W\text{-}1)}$ with size $(2H\text{-}1 \times 2W\text{-}1)$ for a scaling factor of 2. The missing pixels are interpolated in a two-stage filling process. The original pixels from the LR image are depicted in Fig. 1 as solid black circles and the missing pixels are depicted as squares and white circles. The interior white circles are interpolated in the first stage, whereas the square aligned pixels are interpolated in the second stage. Pixels interpolated in the second stage have two orientations marked by gray squares and black squares; interpolation of gray square missing pixels is shown in Fig. 1(f).In the first stage, in a 7×7 window around every missing interior pixel p, the two orthogonal directional gradients $G1$ and $G2$ are computed in the diagonal directions 45 and 135, respectively, as in (1) and (2). Gradients used to compute both $G1$ and $G2$ are depicted by Figs. 1(a) and 1(b), respectively. The edge direction at the missing pixel is detected by comparing the ratio of $G1$ and $G2$ by using a threshold th that has been set experimentally to 1.15 based on training. The missing pixel is computed by using the dot product of the intensity values for the four known pixels along the detected edge and the cubic convolution kernel