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Seamless Instant Image Cloning Based on Derivative and Intensity Interpolation ⋆

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Abstract

Seamless cloning of a source image patch into a target image is an important and useful image editing operation. In order to achieve a balance between effect and time-space consuming, this paper applies both guided derivative and closed form intensity interpolation to minimize the disturbing edges and maximize the similarity between target and source images. The image is decomposed into four parts: the approximation parts, the horizonal, the vertical and the diagonal details by discrete wavelet transform. Approximation parts is processed by interpolating pixel values through smoothing the gradient domain and pixel values in other parts are got by direct assignment and linear interpolation. This combination is advantageous in terms of speed, small memory footprint, realizing real time cloning of large regions. We can reduce the time cost to 1/16 of traditional PDE method, Poisson cloning, and achieve better effect for some extreme gradient. In order to define and get the best possible effect, this paper introduces a gradient field measurement method for the evaluation of the quality of cloning. By analysing the cost function that represents the mixture effect we bring about in this paper, our method is proved quite effective in lots of situations.

Keywords: Image Gradient; Guided Derivative Interpolation; Discrete Wavelet Transform; Mean-value Coordinates; Seamless Instant Cloning

1 Introduction

Image editing encompasses the processes of altering images, whether they be digital photographs, traditional photochemical photographs, or illustrations. A wide variety of image and video editing can be accomplished by gradient domain techniques which operate directly on gradient field of an image. Because the gradient field of the membrane has minimal L^2 norm, it is advantageous in dealing with general oscillating patterns [1]. Many classic PDE models such as P-M anisotropic diffusion model and Mumford-Shah model play their influential roles in image processing. Here we focus on both Poisson cloning and other techniques such as discrete wavelet transform and MVC method to improve processing speed and applicability, in a seamless and instant way.

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There are two main principal of image cloning: PDE method and linear interpolation smoothing. The first is to recalculate the value of pixels by minimize the derivatives difference of mixed image; the second is to minimize the seam artifacts by smoothing the transition between the images. Poisson cloning is a typical PDE approach and MVC method is an effective linear interpolation one. All PDE techniques, including Poisson cloning [2], eventually solve a large sparse linear system resulting from the discretization of Poisson equation. MVC method [3] is a coordinate-based approach that performs seamless cloning without having to form and solve systems of equations. With the help of other related operations, adaptive mesh, this method is fast, straightforward to implement and use a small memory footprint. Its limitation lies in the processing of extreme gradients. The reason is that MVC membrane in each half of the shape is affected by values along the boundary of the opposite half even though they are totally different.

In this paper, we apply an approach, discrete wavelet transform, that decomposes the global image into four parts, approximation parts, the horizonal, the vertical and the diagonal details [4]. In this way, information loss is avoided because DWT can reconstruct the image exactly. We deal with the approximation parts using gradient domain techniques and other parts by closed form intensity interpolation. Scale of the linear equation was reduced to 1/16 of before and direct interpolation becomes more simple because the coefficients of discrete wavelet transform in detail parts are mostly zeros. What's more, the consequence of editing extreme domains improves.

After presenting the principal of discrete wavelet transform, derivative interpolation and intensity interpolation, we go on to show some applications of our approach. The quality of image cloning is measured by the similarity of the source image and the target one and the visibility of the seam between the stitched image.

Gradient domain methods

It is well known that gradient of intensity, suppressed by Laplace operator, can be superimposed on an image without notification. What's more, a scalar function on a bounded area is uniquely determined by its values on the boundary and its Laplacian in the interior. So, the Poisson equation can be solved numerically to achieve seamless filling of the domain.

A guided interpolation framework, with the guidance being specified by the user was proposed. Gradient domain methods modify images by manipulating the gradient field to make the difference unnoticeable. This reconstruction from the modified gradient field typically need to solve the Poisson equation, subject to some boundary conditions. In this paper, we deal with image interpolation using a guidance vector field.

Mean-value coordinates method

Traditionally, solving the Poisson equation is computational and memory intensive. Mean-value coordinates method avoids solving a linear system by direct intensity interpolation and improve the time efficiency greatly taking advantage of adaptive mesh and hierarchical boundary sampling. These coordinates were specifically designed for constructing smooth harmonic-like interpolates and are given by a simple closed-form formula.

2 Seamless Image Cloning Merging Both Derivative and Intensity Processing

Discrete wavelet transform is used to divide a given function into different scalar components and the wavelet transform is the presentation of the function by wavelet. Usually, each component can be studied with the resolution that matches its scalar. As for the 2-D discrete wavelet transform, an image can be divided into four parts, the approximation parts, the horizonal details, the vertical details and the diagonal details. Wavelet transforms have advantages over traditional Fourier transforms for representing functions that have discontinuities and sharp peaks, and for accurately reconstructing finite, non-periodic or non-stationary signals.

The discrete wavelet transform of signal X is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response g resulting in a convolution of the X and g.

$$y_{low}[n] = (X * g)(n) = \sum_{k=-\infty}^{\infty} X[n]g[n-k]. \tag{1}$$

The signal is also decomposed simultaneously using a high-pass filter h:

$$y_{high}[n] = (X * h)(n) = \sum_{k=-\infty}^{\infty} X[n]h[n-k]. \tag{2}$$

As for the 2D discrete wavelet transform, the above process repeated twice to generate four parts, the approximation coefficients, the horizonal details, the vertical details and the diagonal details coefficients. As follows, along n direction,

$$v_{1,L}[m,n] = \sum_{k=0}^{k-1} F[m, 2n-k]g[k],\ v_{1,H}[m,n] = \sum_{k=0}^{k-1} F[m, 2n-k]h[k],$$

and along m direction,

$$f_{1,LL}[m,n] = \sum_{k=0}^{k-1} v_{1,L}[2m-k, n]g[k],\ f_{1,HL}[m,n] = \sum_{k=0}^{k-1} v_{1,L}[2m-k, n]h[k],$$

$$f_{1,LH}[m,n] = \sum_{k=0}^{k-1} v_{1,H}[2m-k, n]g[k],\ f_{1,HH}[m,n] = \sum_{k=0}^{k-1} v_{1,H}[2m-k, n]h[k].$$

The dimension of input matrix is $N \times N$ and of the four output matrix is $\frac{N}{2} \times \frac{N}{2}$. According to frequency difference, we divide and realign the components in order to implement, image processing and eigenvalue extracting more efficiently. One of the most important characteristic of discrete wavelet transform is no information lost during the process and the image can be reconstructed with details remained. For $f_{1,LL}$, the approximation parts, we employ Poisson cloning method to smooth the gradient field by guided interpolation.

Guided derivative interpolation

Let S, a closed subset of R^2, be the image definition domain, and let Ω be a closed subset of S with boundary $\partial\Omega$. Let $f^*_{1,LL}$ be a known scalar function defined over S except the interior of Ω and let f be an unknown scalar function defined over the interior of Ω. Finally, let v be a vector field defined over Ω. The minimization problem is

$$min \iint_{\Omega} (\Delta f_{1,LL} - v)^2 \, \mathrm{d}p, with f_{1,LL,\partial\Omega} = f^*_{1,LL,\partial\Omega}, \tag{3}$$

whose solution is the unique solution of the following Poisson equation with Dirichlet boundary conditions:

$$\Delta f_{1,LL} = div\mathbf{v}, over\Omega, with f_{1,LL,\partial\Omega} = f^*_{1,LL,\partial\Omega}, \tag{4}$$

where $div\mathbf{v} = \partial u/\partial x + \partial u/\partial y$ is the divergence of $\mathbf{v} = (u, v)$.

For discrete images, the problem can be discretized naturally using underlying discrete pixel grid. The idea of this paper is based on simple idea of central difference between rows for horizontal gradient and difference between columns for vertical gradient.

$$\frac{\partial f}{\partial x} \doteq \frac{f(x+1,y) - f(x-1,y)}{2}, \; \frac{\partial f}{\partial y} \doteq \frac{f(x,y+1) - f(x,y-1)}{2}.$$

The finite difference discretization of (4) form a classical, sparse, symmetric positive-definite system. We use UMFPACK to solve the linear systems.

According to the characteristics of discrete wavelet transform, zeros spread all over the coefficients of details parts. There is no need to solve the Poisson equation for the time and space consuming brought about by solving linear equation. We decide to use mean-value coordinates method, a closed formula, to replace Poisson equation. It is quite advantageous for array assignment because of zeros existence.

Closed form intensity interpolation

Consider a closed 2D polygonal boundary curve,

$$\partial P = (P_0, P_1, \ldots, P_m = P_0), P_i \in R^2.$$

p_0 is in the center and $P_i\,(i = 1, \ldots, m-1)$ are around P_0. Now we want to find sets of weights so that

$$\sum_{i=1}^{m-1} \omega_i p_i = p_0, \; \sum_{i=1}^{m-1} \omega_i = 1. \tag{5}$$

Proposition 1 ([5]) The mean-value coordinates of a point $x \in R^2$ with respect to ∂p are given by

$$\lambda_i(x) = \frac{\omega_i}{\sum_{j=0}^{m-1} \omega_j}, i = 0, \ldots, m-1, \tag{6}$$

where $\omega_i = \dfrac{\tan(\alpha_{i-1}/2) + \tan(\alpha_i/2)}{\| p_i - x \|}$, and α_i is the angle $\angle\, p_i x p_{i+1}$.

For Poisson equation $\Delta f = div\nabla g$ with $f_{\partial p_t} = f^*$, solving the above PDE is equivalent to solving the Laplace equation:

$$\Delta \widetilde{f} = 0, \text{ with } \widetilde{f}_{\partial p_t} = f^* - g. \tag{7}$$

The final result of the cloning is simply defined

$$f = g + \widetilde{f}, \tag{8}$$

where g and f^* denote the source and target image intensities over their respective domains. In fact, this method aims to interpolate the difference $f^* - g$ between the target and source images on the boundary across the entire region.

Adaptive mesh For practice purpose, We use CGAL library to generate the adaptive mesh. The mean-value coordinates method are only used to compute each mesh vertex and values of other points are got through linear interpolation of the three values at the vertices of the containing triangle.

We apply the mean-value coordinates method to $f_{1,HL}, f_{1,LH}\, and\, f_{1,HH}$. Then we reconstruct the signal with the processed coefficients without loss of information.

There have been lots of works proposing fast Poisson solvers on GPU. The most famous one is the UMFPACK developed by University of Florida. With both of the two techniques, the total cost of the computation roughly reduces to about 1/16 of the Poisson cloning.

Main algorithm

(1) Apply Discrete Wavelet Transform to divide the image into four parts

(2) Solve a small Poisson equation about approximation parts.

(3) Use MVC method on other parts.

(4) Reconstruct from the processed coefficients.

3 Application and Performance

In this section, we show the outcomes of direct composite, Poisson cloning, Poisson cloning on the approximation parts without MVC on other parts and our method. By comparing the time consuming and pixel values difference of different method, we conclude that our method can achieve good effect by less time consuming.

Analysis for time consuming As we apply UMFPACK to carry on LU decomposition, the complexity of LU decomposition is reduced to about $O(n)$ from $O(n^3)$ for the sparse matrix. Complexity of solving a triangle linear system of dimension n is $O(n^2)$. Through discrete wavelet transform, the approximation part become an image of $\frac{m}{2} \times \frac{n}{2}$ (m is the width, n is the length of the image). The linear system produced by Poisson cloning is reduced to $\frac{m}{2} \times \frac{n}{2}$ from $m \times n$, so the complexity of solving the related triangle linear system is reduced to $(m^2n^2/16)$ from m^2n^2. Besides, the time consuming of discrete wavelet transform is $O(n)$, So overall the complexity was reduced to about 1/16 of before by our method. The larger the image is, the more precise the ratio converges to 1/16. As is shown in the Fig. 1.

Table 1 description: as the image becomes larger, the speed-up of our method becomes more obvious.

Table 1: Running time of different methods

Methods	Pear	Pigeon	Gap
Size (pixels)	720 000	80 000	60 000
Our Method	106.16s	1.69s	0.93s
Poisson Cloning	907.49s	3.99s	1.49s
Speed-up	8.55	2.36	1.60

Here, we define a measurement function. We calculate the pixel variation Va along the gradient field around the boundary and compared our method with Poisson cloning. Finally we conclude that the processing ability of our method is similar with Poisson cloning.

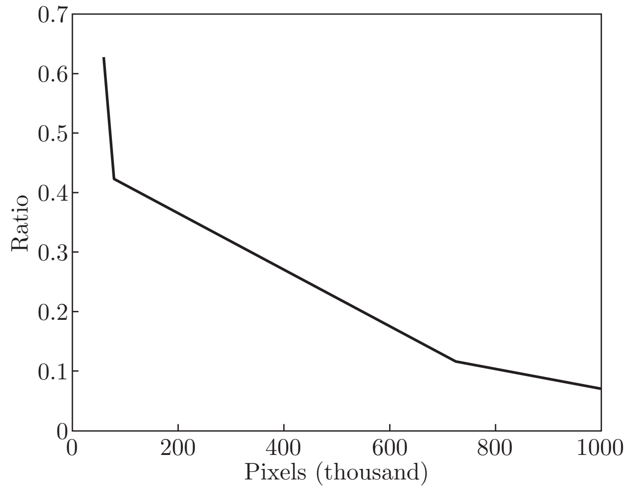

Fig. 1: The larger the image is, the more precise the ratio converges to 1/16

$\nabla f = \left(\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right)$, f is the pixel values in target image. Then we calculate the average pixel variation along the gradient field around the boundary using Va,

$$Va = \left|\frac{\partial f}{\partial x}\right| + \left|\frac{\partial f}{\partial y}\right|,\ AVa = \sum_{i=1}^{n} Va/n,$$

where n is the number of pixels around the boundary.

So in a typical scenario, the effect of our method is difficult to tell apart from Poisson method. But time consuming is reduced to about 1/16 of Poisson method. In extreme gradient, our method performs better than MVC method. As for the domain with unregular small dotted textures, Poisson cloning spreads the difference all over the domain, which may result in unnatural effect. On the contrary, the maintenance of textures existing in the horizonal, vertical and diagonal details can preserve the original characteristics.

For Fig. 2 and Fig. 3, (a) Copies and pastes the selected domain directly on the target image. (b) Edits the Composite Image with Poisson cloning method. (c) Applies Poisson cloning on approximation parts without MVC on other parts, (d) Our Method.

For Fig. 4 and Fig. 5, (a) Represents the pixel variation of Poisson cloning along the gradient field around the boundary. (b) Represents the pixel variation of our method along the gradient field around the boundary. Horizontal coordinates represent each pixel at the specified location.

For Fig. 6-Fig. 7, (a) Copies and pastes the selected domain directly on the target image. (b) Edits the composite image with Poisson cloning method. (c) Applies mean-value coordinates method on the selected area. (d) Our method. Horizontal coordinates of Fig. 7 represent each pixel at the specified location.

4 Further Discussion

We continue to decompose the approximation part at level 1 into four parts and get an image that is 1/16 size of the original. We hope to achieve a satisfying effect solving a smaller scale equation. However, the consequence is not pretty good (Fig. 8). The reasons are as follows: (1)

Fig. 2: Obviously, Our method (d) improves greatly compared with the direct composite one (a) and is difficult to tell apart visually with Poisson cloning (b)

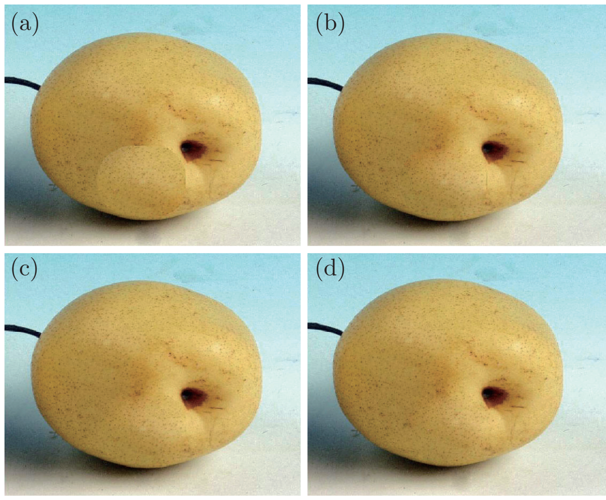

Fig. 3: Right upper corner of processed part of (c) is still visually different with the source image. Effect of (b) and (d) have visually no difference

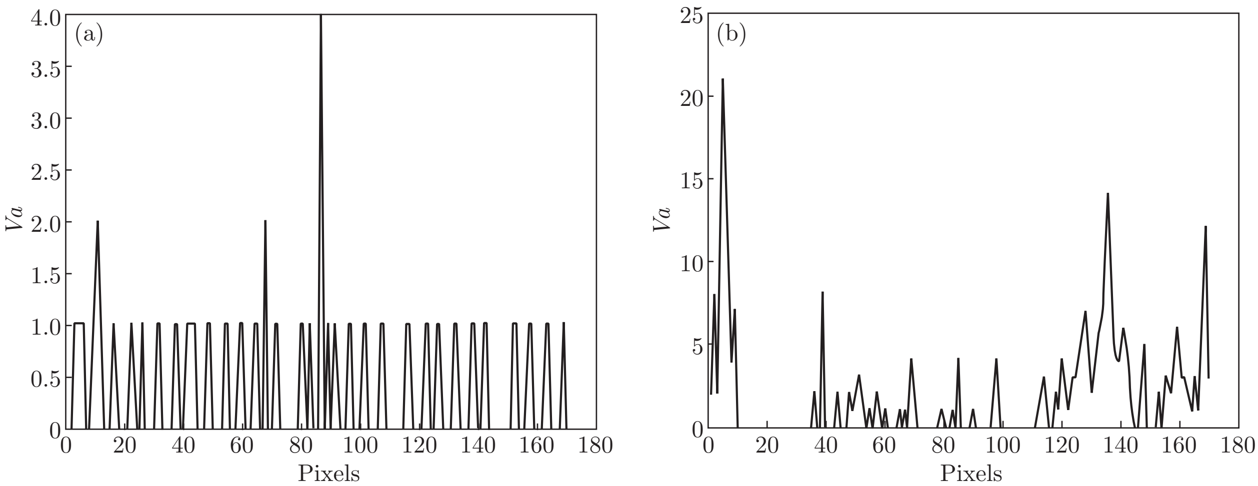

Fig. 4: Boundary variation of Poisson cloning (a) is much regular than our method (b), but ranges of changes are both limited to a small value. (a) AVa is 0.41 (b) AVa is 1.02. The visual effect are very similar. This is the Va picture for Fig. 2 above

1/16 of an image contains too little information to represent the whole one. (2) It is difficult to tell apart the border of the smaller image and the processing of the edge seems less successful. (3) This kind of try makes the advantages of Poisson cloning less apparent and brings about new problems, such as edge detection.

5 Conclusion

Through discrete wavelet transform, total cost of computation is reduced to about 1/16 of the original Poisson editing. MVC has limited processing ability for extremely concave regions because each part of the shape is affected by values along the boundary even though they are extremely

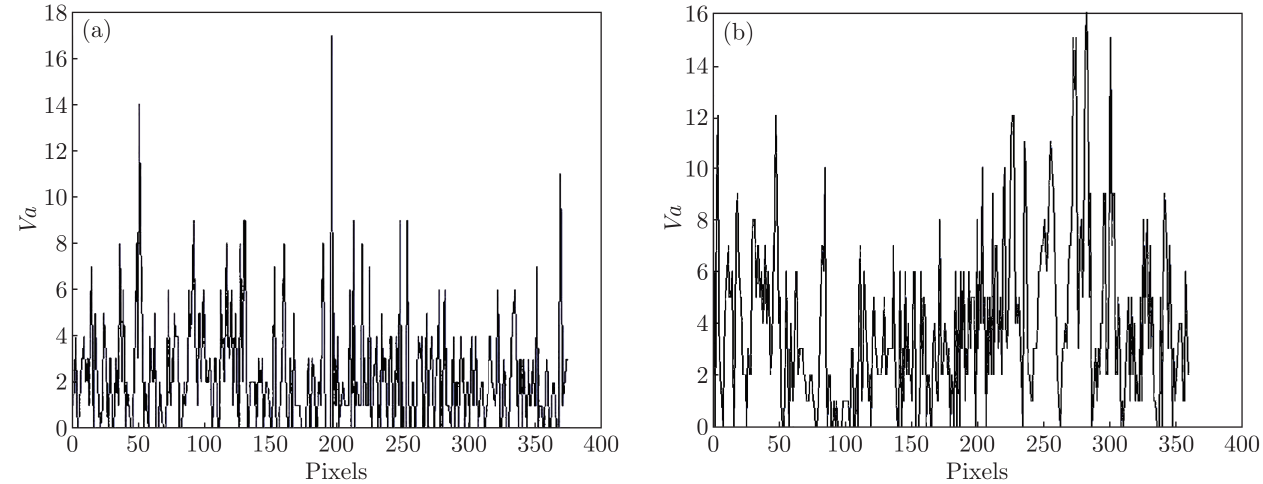

Fig. 5: Pixel changes around the boundary are very similar along the gradient field of the Poisson cloning (a) and our method (b). (a) AVa=2.31, (b) AVa=3.73. Their processing ability is very similar. This is the Va picture for Fig. 3 above

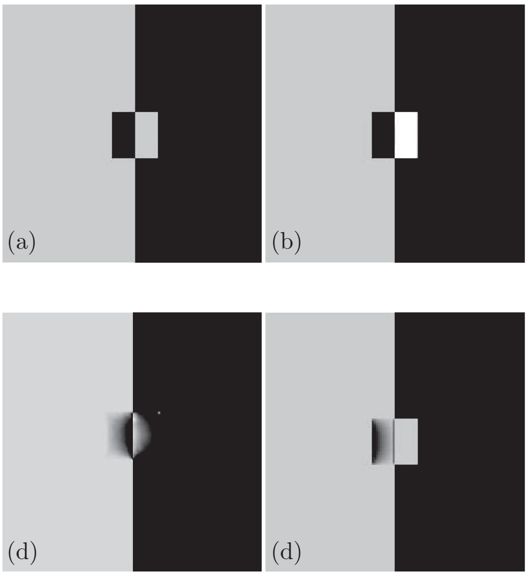

Fig. 6: (b) Contradistinction because more obvious. (c) Irregular selected domain is generated. (d) The whole image is regular and smooth relatively. For images with extreme gradient domains, Poisson cloning and MVC method lead to apparent irregular membranes. But our method behaves well dealing with these situations

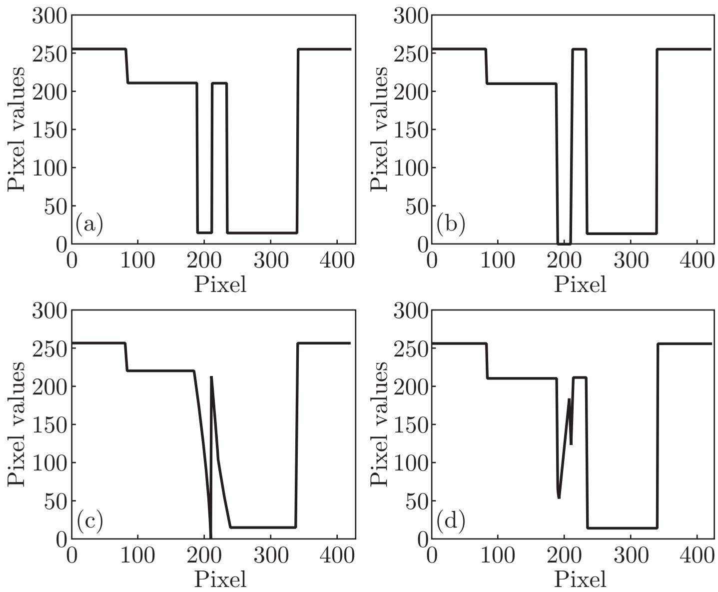

Fig. 7: Volatility trend along a specified direction. (a) Interior is smooth and boundary is apparent. (b) The difference between white and black becomes more obvious. (c) Original characteristics are gone. (d) Most characteristics are kept and the difference is less obvious. It's obvious that our method can maintain more original characteristics than MVC

different. Our method can make these situations much better even though Poisson cloning and MVC Method cannot handle them with good effect. It can preserve textures missing during MVC processing, because Poisson cloning maintains image details and the approximation part contains most of the image information. However, the limitation still exists such as the time consuming compared with mean-value coordinates method and its applications have to depend on the texture

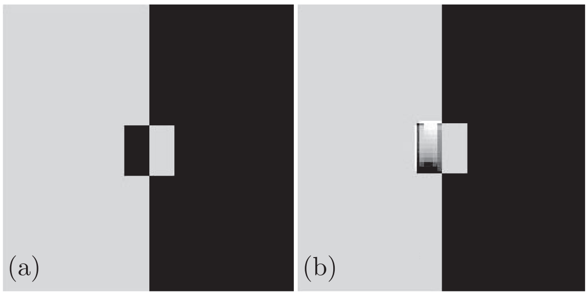

Fig. 8: (a) is the composite image. (b) edits the level 2 approximation parts of discrete wavelet transform with Poisson cloning method. The boundary is not easy to distinguish compared with other methods

similarity.

6 Future Work

Our current implementations are restricted to image cloning and we are eager to apply our method to video editing. Thus, we have to solve the problem that concerns with the changing source images. We plan to search for different direct intensity interpolation method to replace mean-value coordinates and achieve better effect, such as cubic spline with both pixel values and derivatives in consideration. We should also explore the possibility of performing cloning of electromagnetic fields or other complicated data levels.

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