An Image Processing Method: Edge-guided Directional Walk Mean Smoothing

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Abstract. Image denoising is an important computer vision task, it is also the basis of many other high-level vision tasks. Recently, various image denoising algorithms have proposed, such as BM3D, sparse representation and deep learning, that have achieved impressive performance in AWGN denoising or blind denoising tasks. However, when dealing with Dongba painting (A traditional painting from China’s ethnic minorities), there are problems that Dongba painting have blurred edges and faded colors, it is important to retain its original style when denoising. In this paper, we propose a novel image post-processing technique termed edge-guided directional walk mean smoothing (EDWMS), it can effectively calculate the mean of pixels along different directions then obtain denoised image with sharp edge. Experiments show that the proposed EDWMS outperforms compared algorithms in both edge sharpness and color saturation.

Keywords: Edge-guided; Directional walk; Image denoise; Post-processing; Dongba painting.

1. Introduction

In image restoration and enhancement, image denoising is a fundamental and crucial problem, the problem described as follow: y=x + v, where x is a ground truth image, and v is the noise, then y can be considered as an image with noise, image denoising’s objective is to estimate ground truth x from y. In recent years, non-local [1], sparse representation [2], external priors [3,4], and deep learning-based [5-10] methods have an enormous application range in image denoising and have yielded excellent results. In image denoising, there are two main categories of noise, namely additive white Gaussian noise or real noise, and Dongba painting is a style of China’s ethnic minorities (show in figure 1), Obviously, its noise belongs to the latter category. Dongba paintings are mainly based on lines and colors, using lines to depict people and images (such as people, animals, etc.), which incorporates religious artistic characteristics, at the same time, rich colors are used to express the emotion and environment of the characters. However, due to the influence of various factors such as painting materials, pigments, environment, etc., problems such as color saturation distortion and noise destruction occurred in the process of preservation and digital display, which destroyed the original visual and artistic effects of Dongba painting. Certainly, it is easy to aware of restoring Dongba painting by image denoising methods. Nevertheless, through experiments, we found that the problem of color saturation distortion in Dongba painting is not completely solved, and the edges are more blurred.

In order to obtain sharper edge and higher color saturation for the denoised image, inspired by mean filter, we present a new image post-processing technique termed edge-guided directional walk mean smoothing. The proposed method not only refers to the neighborhood information of the pixel, but also considers the influence of the direction in the smoothing process. In mean filter, only the neighborhood information of pixels is considered, it also blurs the edge while smoothing the noise. The presented
EDWMS method introduces the edge information of denoised image to guide the calculation of the directional walk mean instead of calculating the mean of pixels within a fixed scale. The purpose of introducing edge is to avoid blindly calculating the mean of all pixels in the neighborhood, because of which also includes edge.

![Figure 1.](image1.png)  
(a) and (b) is Dongba painting.

Traditional filtering algorithms filter images based on local information. Non-local mean \[1\] divide the image into many image blocks, and no longer only consider the information of the neighborhood, but the information of in larger area. Searching for a group of image patches similar to the reference image block in the area, combine these image patches include reference image patch into a three-dimensional array for collaborative filtering, and make full use of the redundant information of similar patches for denoising.

Sparse representation has been a very interesting research area in the signal or image processing field in recent years. In the theory of sparse representation, it regards the denoising task as a process of continuously optimizing the sparse representation of the image, that is, making the sparse representation sparser, its optimization function can be formulated as:

\[
\hat{\alpha} = \arg \min_{\alpha} \| Q\alpha - y \|_2^2 + \mu \| \alpha \|_0
\]

in equation (1), \(Q\) represents an dictionary, \(\alpha\) denotes the sparse representation of all image blocks in the image, and \(y\) represents a noisy image, \(\mu\|\alpha\|_0\) denotes a regularization term and \(\mu\) is a regularization factor, which denotes the number of zero elements in \(\alpha\), the more zero means the sparser. Getting the best sparse coding of the image block by minimizing the objective function, and then approximate the clear image through the sparse representation. In image denoising, its purpose is to use as few atoms as possible to represent the image information in a given super-complete dictionary, as the same time, constantly update the dictionary, so that a more concise representation of the image can be obtained, and we can more easily obtain the estimate of the clean image from noisy image. \[2\] introduces a trilateral weighted matrices based on the data and regularization items of the sparse coding framework to represent the real noise and image prior statistical characteristics to remove the real noise. Different from the method based on image self-similarity, the image external priors method is no longer limited to the internal similar blocks of the image, but focuses on the external prior knowledge. \[3\] learns a simple Gaussian mixture prior from a lot of clean natural images. \[4\] combines the external patch prior with the internal self-similarity, and uses the external image block prior to guide the clustering of the internal familiar blocks. Recently, With the development of deep learning \[5-10\], deep learning has become increasingly popular in image denoising filed. Researchers use deep learning to abstract rich features and learning a mode to restructure clear images from noisy images in feature extraction.

2. Proposed Method
In this section we will introduce the method of this paper, including the basic concepts, formulas, and how the method works.

2.1. Mean Filter
Mean filter is a typical linear filtering algorithm, it gives a template centered on the target pixel and replaces the target pixel with the arithmetic mean of all the pixels in the template, the template includes
the neighboring pixels (8 pixels around the target pixel as the center constitute a filter template, including the target pixel itself).

\[ f'(p_o) = \frac{1}{mn} \sum_{i=0}^{m-1} f(p_i) \]  

In equation (2), \( f \) represents the pixel value and \( f' \) denotes the updated, \( p_o \) is the target pixel in the center of the template (for convenience, we assume that the template is a square), and \( p_i \) is the \( i \)-th pixel starting from \( p_o \) in the template. Equation (2) is the mathematical representation of mean filter. Mean filter itself has inherent defects, that is, smaller templates have better detail but less noise reduction, while larger templates have better noise reduction but lose detail, as shown in figure 2. In other words, mean filter cannot protect the image details well when denoising image.

![Figure 2](image-url)

Figure 2. (a) original image; (b) noisy image (\( \sigma =10 \)); (c) result of the mean filter, we can see that the edges are blurred; (d) our results.

2.2. Edge Guidance and Directional Walk

Mean filtering is a typical image processing method using neighborhood information, advanced version and variant of it still play an important role in visual tasks, due to its inherent shortcomings, it will also blur the edge when smoothing Dongba painting. So how can we improve it? Next, we will give a solution to this problem. While we all know that fixed-size templates are an important reason for mean filtering to produce undesirable results, fixed-size templates ensure that the pixels within the template's coverage are as relevant as possible, because the neighborhood detail within a fixed region is implied in the template. Therefore, the concepts of edge guidance and directional walk proposed respectively for neighborhood and fixed region. We utilize the edge to control the calculation range and in order to make the method simpler and more efficient, we design a calculation method called directional walk. Figure 3 demonstrate the calculation process of mean filter and our method in the edge area and non-edge area respectively, the black squares and white squares in the figure 3 represent edge and non-edge, respectively, and the square marked with the letter P is the target pixel. Assuming that the size of an image is \( M \times N \), the set of all pixels in the image is denoted as \( X \), where \( E \) and \( D \) represent the edge pixel set and the non-edge set respectively, obviously \( E \cup D = X \), and \( x \) represents a pixel in the image \((1 \leq i \leq MN)\), then the directional walking mean smoothing can be expressed as the following form:

\[ \hat{x}_i = \frac{1}{L} \sum_{x_i \in I_j} x_j \quad s.t. \quad x_j \in I_j \]  

where \( \hat{x}_i \) denotes the updated target pixel \( x_i \), and \( I_j \) represents the set of all pixels from \( x_i \) to \( x_j \) (of course also including \( x_i \) and \( x_j \)), \( L \) indicates the number of elements in the set \( I_j \), all in \( I_j \) are non-edge pixel, that is, \( I_j \cap D \). In particular, the subscript \( i \) represents the target pixel, and \( j \) represents the non-edge point before the first edge point encountered starting from \( x_i \), this just reflects the role of edge guidance. As in equation (3), we only set one direction, but in the implementation of the algorithm. We recommend setting multiple directions, because multiple directions mean more neighborhood information is exploited and better effects can be obtained. To consider neighborhood details in multiple directions, we rewrite equation (3) as:
\[ \hat{x}_i = \frac{1}{S} \sum_d \sum_k x_{i,k}^d \quad \text{s.t.} \quad x_{i,k}^d \in I_g^d \]  

where \( d \) denotes direction, and \( S \) indicates the number of non-edge pixels in all directions. By introducing edge guidance and orientation calculation, the problems caused by fixed templates can be avoided. In order to exploit our EDWMS method in practical applications, we propose an application framework, the overall framework is presented in figure 4 below.

3. Experiments

We evaluated the performance of the proposed EDWMS method on Dongba painting. We compared the proposed method with some state-of-the-art denoising methods, including BM3D [1], PCLR [4], TWSC [2].

3.1. Related Settings

In figure 4 we depict the flowchart of our framework, its main components include three parts, namely: pre-denoising, edge extraction and EDWMS. We will introduce how to set these three components in the experiment. **Pre-denoising**: pre-denoising is a basic step of the method in this article, it can be any other denoising method. This experiment uses TWSC [2] for pre-denoising. Of course, our results will be compared with the results of TWSC [2]. **Edge extraction**: edge extraction is also a step of the method in this paper and we can obtain clear image edges with XDoG [11] or others. In experiment, we use XDoG [11], which can achieve better results. **EDWMS**: in this step, the parameter that needs to be set is the direction \( d \). The more directions, the richer the neighborhood information contained, and the higher the quality of the final results obtained by the method.

3.2. Results on Dongba Painting

In this subsection, we set up two experiments for different conditions, namely experiment A and experiment B. In experiment A (figure 5), we compared the results of our framework with BM3D [1], PCLR [4], and TWSC [2]. It should be noted that the pre-denoising in framework uses TWSC [2]. The purpose of experiment A is to illustrate the better effect of our framework. It can be seen from (b) to (d)
in figure 5 that the results of the other three methods are blurry at the edges of the white and red areas. In contrast, our results are clearer than the others and have better visual effects.

Figure 5. Results of experiment A.

In experiment B, we conduct comparative experiments by adjusting the internal components of our framework. We alternately used BM3D [1], PCLR [4], and TWSC [2] methods in pre-denoising, and compared their pre-denoising results with the final framework. In figure 6, (d) is the original image, and each column in two rows to the right of (d) are the results of the two stages of our framework based on different pre-denoising methods, where (a), (b), (c) are the outcomes of pre-denoising using BM3D [1], PCLR [4], and TWSC [2] respectively; (e), (f), (g) corresponding to (a), (b), (c) are the final outcomes of proposed framework. Through experimental comparison, we can find that the result of framework is always better than the result of pre-denoising. This once again proves the advantages of EDWMS in the denoising of Dongba painting compared with other denoising algorithms.

Figure 6. Results of experiment B.

4. Conclusion
In the denoising task of Dongba painting, it is very important to protect edges and restore color, because edge and color are the most important embodiment of Dongba painting's artistic style. In this paper, we propose a mean smoothing method based on edge guidance and directional walk. Experiments have proved that our method can make the blurred edges in the denoised picture clearer, remove colour blocks, and improve colour saturation. Of course, the EDWMS method still has shortcomings, for example, its results are restricted by the edges. If the edges are not clear, the effect of EDWMS will be weakened. At the same time, the EDWMS method can be further improved, for example, the linear area of directional walking can be considered to be a polygonal area that contains more neighbourhood information.

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