Adaptive Algorithm in Image Denoising Based on Data Mining

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Abstract

An adaptive filtering algorithm based on data mining is proposed for image denoising when an image is merged by pepper-and-salt noise. It can adjust the rotating mask size based on the noisy density in the input image so that it raises greatly the computing speed; On the other hand, the algorithm can determine the mask coefficients based on the noise case so that it reduces largely the error rat; And then it is more effective than other methods when the image has a higher noisy density. Experimental results indicate that the adaptive filtering is superior.

Keywords: Data mining, Image denoising, Pepper-and-Salt Noise, Noisy density, Adaptive filtering

1. Introduction

Image mining is rapidly gaining attention among researchers in the field of data mining, information retrieval, and multimedia databases because of its potential in discovering useful image patterns that may push the various research fields to new frontiers. Image mining denotes the synergy of data mining and image processing technology to aid in the analysis and understanding in an image-rich domain. It is an interdisciplinary endeavor that draws upon expertise in computer vision, image processing, image retrieval, data mining, machine learning, database, and artificial intelligence. While some of the individual fields in themselves may be quite matured, image mining, to date, is just a growing research focus and is still at an experimental stage. Broadly speaking, image mining deals with the extraction of implicit knowledge, image data relationship, or other patterns not explicitly stored in the images and between image and other alphanumeric data. For example, in the field of archaeology, many photographs of various archeological sites have been captured and stored as digital images. These images, once mined, may reveal interesting patterns that could shed some lights on the behavior of the people living at that period of time [1].

Figure 1 shows the image mining process. The images from an image database are first preprocessed to improve their quality. These images then undergo various transformations and feature extraction to generate the important features from the images. With the generated features, mining can be carried out using data mining techniques to discover significant patterns. The resulting patterns are evaluated and interpreted to obtain the final knowledge, which can be applied to applications [1].

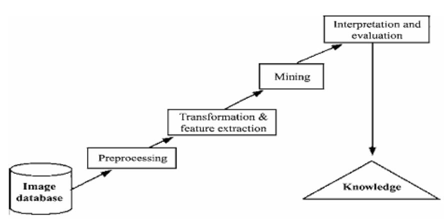

Fig. 1: Image mining process [1]

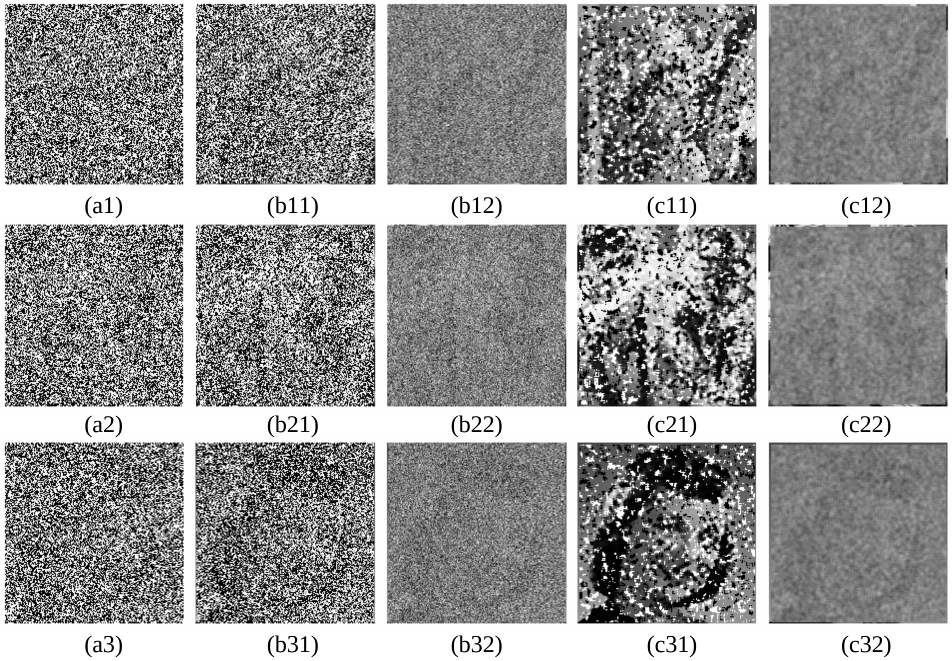

Fig. 2: Image denosed by median and mean filter with size 3×3 and 11×11
(a1), (a2) and (a3) is the image with noisy density 0.9
(b11-b31) and (b12-b32) are the denoised image by median and mean filter with size 3×3
(c11-c31) and (c12-c32) are the denoised image by median and mean filter with size 11×11

Image denoising is not only an old but also still a problem discussed, see [2] - [11]. An important task of mathematical image processing is image denoising, see [6]. The contents include the noise removing from various images, such as satellite and medical images, and by various methods. In typical images the noise can be modeled with either a Gaussian ("normal"), uniform, or pepper-and-salt ("impulse”) distribution, see [7].

Traditional image denoising methods, such as mean filters and median filter, are ineffective when the noise density in an image is very high, see Figure 2 serial (b). Though extending the size of filter can improve the effect to removing noise, it brings out the serious problem of blurring sharp edges in the image, see Figure 2 serial (c). In the opinion of the image edges, the smaller the operating neighborhoods are, the better the image quality is. But on the other hand, the effect of removing noise is lower.

In this paper, we investigate the disadvantage of current denoising methods and the characters of pepper-and–salt noise and propose an adaptive filtering algorithm based on spatial distribution structure by means of data mining thinking. The algorithm can preserve the non-noise pixels and avoid blurring the edges. It can adjust the rotating mask size based on the noisy density in the input image by itself; On the other hand, the algorithm can adjust the rotating mask coefficients based on the noise case by itself. All in all, the adaptive algorithm overcomes the shortcomings of median and mean filtering, such as blurring edges and averaging noise, takes in the thought of picking noise and neighborhood averaging, and adds the adaptive adjusting method. Experimental results indicate that the adaptive filter is superior.

2. Algorithm

2.1. Preprocessing-detecting noise pixels

The current denoising methods have mostly a mistake for understanding pepper-and-salt noise. In fact, it may be easily detected from the noisy image because of the contrast anomalies, see [12]. Figure 3 (b) shows the histogram of an image with pepper-and-salt noise. Comparing the histogram of noisy image with the one of image without noise, we can identify the non-noise pixels. The non-noise pixels should be preserved and noisy pixels will be replaced by some correct value.

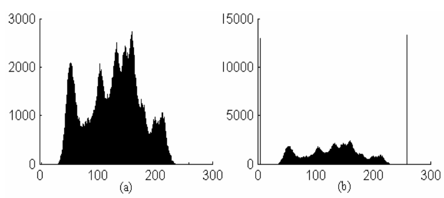

Fig. 3: Histogram of source image and noise image

2.2. Determining the rotating mask size

In fact, filtering can be achieved by moving of the rotating mask. Giving an image $f(x,y)$ and a rotating mask h of size $(2k+1)(2k+1)$ with coordinates varying from $-k$ to k horizontally and vertically, the filtering image $\tilde{f}(x,y)$ is defined by

$$\tilde{f}(x,y) = median\{f(x+i,y+j) \times h(i,j)|_{h(i,j)\neq 0}\}, \quad (1)$$

where $i, j = k \ or -k$. Generally, $h(i, j)$ and k both are a certain value, but here, the filter h that we propose and k both are variable.

Assume the pixel p with coordinates (x, y) under consideration to be a non-noise pixel, seeing Figure 4(a), then the size of h is 1×1 , furthermore $h(0,0)=1$ is the unique coefficient, and the k , as above equation (1), is 0. If the pixel p with coordinates (x, y) is a noisy pixel under consideration, see Figure 4(b), p' with coordinates (x', y') is the nearest non-noise pixel to p with the Chessboard distance D_8 . D_8 is defined as follows

$$D_8(p,p') = \max\{|x-x'|,|y-y'|\}, \quad (2)$$

seeing equation (2.43) in [13], then $k = D_8$. h possesses size $(2k+1)(2k+1)$ and consists of $(2k+1)(2k+1)$ coefficients.

The mask coefficients $h(i, j)$ are defined as follows:

$$h(i,j) = \begin{cases} 1 & if\, f(x+i,y+j) \in (0,255) \\ 0 & otherwise \end{cases} \quad (3)$$

where $i, j \in [-k,k]$, according to equation (2).

Because of k and h both are variable with the pixel p with coordinates (x, y), it is more intuitive that using $k_{x,y}$ represents the region of p or the size of mask h corresponding to pixel p instead of k, and using $h_{x,y}$ expresses the rotating mask at (x, y).

According to all described above, the restoring value $\tilde{f}$ for noisy pixel p is as the following equation,

$$\tilde{f}(x,y)=median\left\{f(x+i,y+j)\big|_{h_{x,y}(i,j)\neq 0}\right\} \quad (4)$$
$$where\ \ i,j=-k_{x,y}\ or\ k_{x,y}.$$

3. Experimental results

Through the full experiments, the original images without noise are the same in Figure 2 and Figure 5 and are showed in Figure 5; and the noise images are also the same in Figure 2 and Figure 5 and are showed in Figure 2. All the images are 512×512 in size and 256 in brightness level.

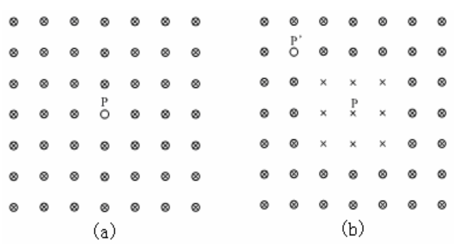

Fig. 4: Schematic diagram of determining filter size for pixel p

× : noisy pixel;

O : non-noise pixel;

⊗ : whether non-noise pixel or noisy pixel.

(a) (aa)

(b) (bb)

(c) (cc)

Fig. 5: Restored images by the adaptive algorithm

- (a), (b) and (c) are the original images
- (aa), (bb) and (cc) are the restored images respectively from the noisy images in Figure 2 (a1),(a2) and (a3)

Figure 5 shows the restored images by the adaptive algorithm. By comparing the results of experiment, it is obvious that the algorithm proposed by this paper is advantaged very well in image denoising, where the noise density arrives 90 percent. Moreover, in order to prove further the effect of adaptive algorithm, we compute the Signal-to-Noise Ratio (SNR), see Table 1. SNR is defined by quation(2.48) in [13].

Table 1: Comparing SNR

Noisy Density	Noise image	Median Filter		Average Filter		Adaptive Filter
		3X3	11X11	3X3	11X11	
0.02	48.3	902	130	259	85	26900
0.2	4.75	251	123	33.3	51.3	1900
0.5	1.9	9.29	104	11.13	20.8	466
0.9	1.06	1.26	3.39	5.04	8.72	94

4. Conclusions and future work

This paper proposes an adaptive filtering algorithm. The algorithm can pick and restore the noisy pixels very well. Because of reserving the non-noise pixels, it avoids blurring and averaging edges and non-noise pixels to the utmost extent. In addition, it is effective when the image noise density is higher or when an image is degraded obviously. It is marvelous that an image can be restored from noisy density 90% above and the adaptive algorithm is successful.

However the adaptive filtering algorithm is inefficient for other noise, such as Gaussian noise. We are planning to improve the algorithm or to investigate a novel algorithm that can be effective for the images with other types of noise next.

5. References

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