Bilateral Filtering using Modified Fuzzy Clustering for Image Denoising

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Abstract:

This paper presents a novel bilateral filtering using weighed fcm algorithm based on Gaussian kernel function for image manipulations such as segmentation and denoising . Our proposed bilateral filtering consists of the standard bilateral filter and the original Euclidean distance is replaced by a kernel – induced distance in the algorithm. We have applied the proposed filtering for image denoising with both the impulse and Gaussian random noise, which achieves better results than the bilateral filtering based denoising approaches, the Perona-Maliks anisotropic diffusion filter, the fuzzy vector median filter and the Non-Local Means filter.

Keywords: fuzzy c means(fcm), Gaussian kernel function, bilateral filter, Persona- Maliks anisotropic diffusion filter, fuzzy vector median filter, Non-Local Means(NLM) filter.

1. Introduction:

Nonlinear diffusion filtering techniques are becoming more and more important in the areas of computer vision and graphics applications. The bilateral filter is a nonlinear diffusion filter proposed by Tomasi *et al.* [2] for smoothing images. It has been adopted for several applications such as high dynamic range image compression [3], image filtering [4] and Monte Carlo noise reduction [8]. Noise removal from a given image is the most important image manipulations, which is the practical problem faced in many digital imaging systems [12]. Among the image Noise-removal techniques, anisotropic diffusion filters are the most relevant to our work [5]. Few of the previous bilateral filtering approaches [3] can reduce both the impulse and Gaussian types of random noise uniformly. In this paper, we propose the bilateral filtering using weighted fcm for reducing impulse and Gaussian types of noise effectively.

According to concretely instances, many segmentation algorithms have been put forward. Among them, image segmentation algorithm based on fuzzy c means is an important algorithm in the image segmentation field [16][17]. It could retain much more information from the original image than hard segmentation methods. Fuzzy c-means clustering algorithm is a representative clustering algorithm. However, FCM algorithm can't realize feature optimization of the sample datas. Meanwhile, with the original FCM algorithm, we can't get satisfactory results because of the influence of the noise.

Document [18][19][20][21] put forward a FCM algorithm based on kernel density function. The original Euclidean distance is replaced by a kernel-induced distance in the algorithm. This new algorithm can effectively analyze many data structures such as non-hyper spherical structure, mixed structure composed of heterogeneous cluster prototypes, and data with noise and so on.

In this paper, using kernel function instead of Euclidean distance, considering spatial information, initializing weight and increasing constraint item, we proposed a weighed fcm algorithm based on Gaussian kernel function for image segmentation. The proposed method can fully consider the influence of noise.

Our proposed fuzzy filtering approach has the following unique features:

• The proposed fuzzy filtering is applied for image Denoising with both the impulse and Gaussian types of noise, which performs better than the existing methods [1], [2], [7], [15].

• The effective weighed fcm algorithm incorporating the fuzzy filtering is developed, which extracts the targeted images from the effectively noisy image.

2. Our Methods:

2.1. Initializing weight

For one image *f(m,n), m=1,….M; n = 1,…N*. Its gray level is L. Then the appearance probability of every gray can be expressed: $h_i = n(i)/M \times N$, $i=0,1,\ldots L-1$ and the following hold: $\sum_{i=0}$ which n(i) represents the number of occurrence of the pixel. i is the gray of the pixel [6].

However, on a 1D gray histogram, the distribution of target and background is overlapped due to the relativity between a pixel and its neighborhood pixels. So with the method of histogram we can't get satisfactory result. Therefore, image's spatial information can be fully used. For example, building a 2D histogram by using the original image and its smoothed image, the target and background can be more easily distinguished than in a 1D histogram.

So the implement method of initializing weight ω_j by using 2D histogram is:

- Using 3x3 or 5x5 template to smoothing *f(m,n)*, we get the smoothed image *g(m,n)*.
- Then initializing the binary array *(s,t)*, s,t = 0,1,….L-1. And every (s,t) is a point on plane SxT.
- Let the number of occurrence of *(s,t)* is n_{st} and the following holds $\sum\sum n_{st} = 1$.
- Then the joint probability density function is $H_{st} = n_{st}$ / MxN, in another word that is the 2D histogram. The diagonal elements of H_{st} express the number of the pixel pairs (s,s).

2.2. Bilateral filtering using weighed fuzzy c means clustering

We prefer the bilateral filter due to the large support size and the fact that they can be approximated quickly with few visual artifacts using a separated kernel [9], [11]. Note that
for the fast automatic filtering case, *kd*(*x*) and *kr*(*x*) are set to zero, then Equation 1 becomes the familiar bilateral filter as follows:

$$h(x,\sigma_d,\sigma_r) = \frac{\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} w'_d(\hat{x},x)w'_r(f(\hat{x}),f(x))f(\hat{x})d\hat{x}}{\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} w'_d(\hat{x},x)w'_r(f(\hat{x}),f(x))d\hat{x}} \quad (6)$$

Unfortunately, neither the standard bilateral filter nor the iterated bilateral one can effectively remove the image noise. This is because the noised pixel values are much larger or much smaller than its neighbor's, the initial estimator *f*(*x*) used in *w' r*(ˆ*x, x, σr*) is far from its true value, thus the noise pixels remain almost unchanged. There are various possible options for estimating *f*(*x*).
We use a weighed fcm to estimate the near-true values ˆ *f*(*x*) from *f*(*x*). It is advantageous to introduce some weighted averaging of samples among similarly valued samples.

From our experiments, we find that the fuzzy median filter (Equation 8) performs well when dealing with impulse or Gaussian distributed noise. Therefore we employ the following ˆ*h*(*x, σd, σr*) (Equation 9) to define our new adaptive bilateral filter:.

$$\hat{h}(x,\sigma_d,\sigma_r) = \frac{\sum_{x\in f(\hat{x})} w'_d(\hat{x},x)w'_r(f(\hat{x}),\hat{f}(x))f(\hat{x})}{\sum_{x\in f(\hat{x})} w'_d(\hat{x},x)w'_r(f(\hat{x}),\hat{f}(x))} \quad (9)$$

Figure 1 illustrates the performance of our fuzzy filtering with the two-tone step image degraded by Gaussian random noise (10%). The results showed that our fuzzy filtered image (Figure 1(e)) has more visually marked improvements, and most closely correlates with the original image (Figure 1(a)).

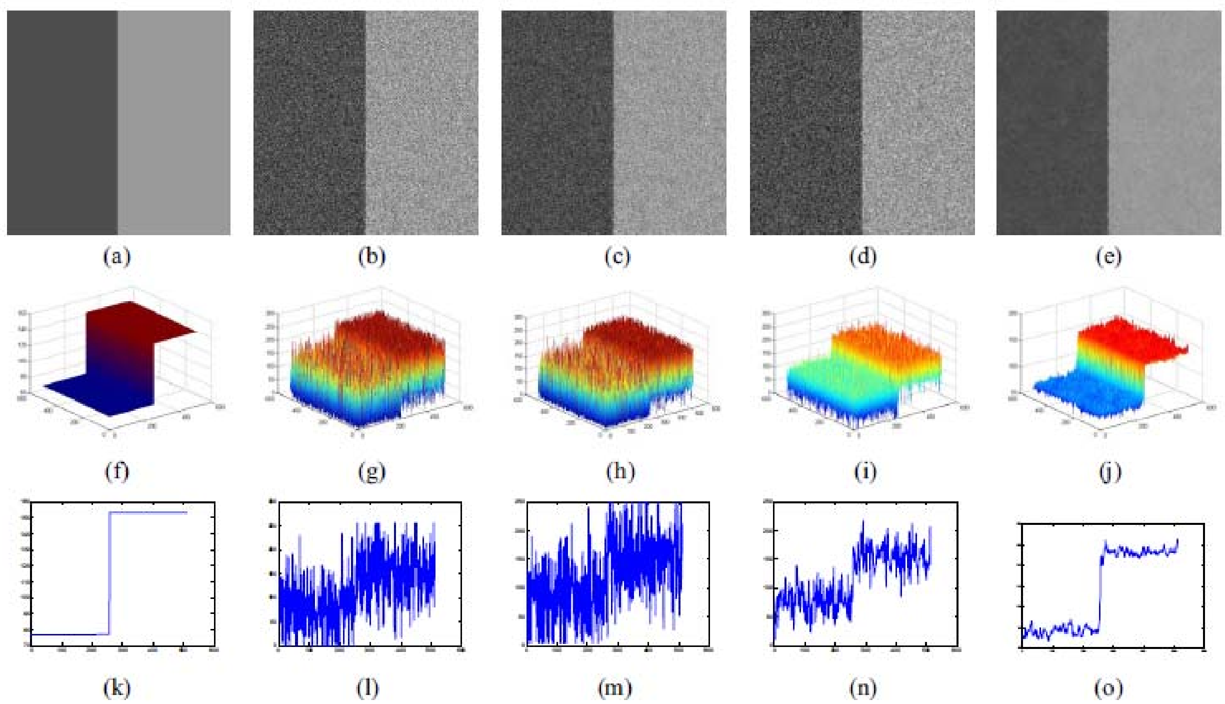

Figure 1. Step test evaluation of our fuzzy filtering (FF), the bilateral filter and median filter performance. (a) original gray-scale test image; (b) step image contaminated with 10% Gaussian random noise; (c) denoised step image using the standard bilateral filter [2] ; (d) denoised image using standard median filter; (e) denoised image using our fuzzy filtering. In both cases in (c) and (e), σd = 16, σr = 0.05; (f)-(j) color contour plots of (a)-(e). (k)-(o) shows 1D example on a random scanline of (a)-(e). The visual marked improvements are clearly shown for the FF denoised image, most closely correlates with the original one.

3. Experimental results

We have applied our proposed bilateral filtering using fuzzy-median for image manipulations, such as image segmentation and Denoising. The experiments are tested on a PC with Pentium IV 1.6GHz CPU + 1024MB RAM.

Experiment one carries out division on a image of lena. Figure 2(a) is a primitive image. Figure 2(b) and 2(c) are the images after division by FCM algorithm and KWFCM algorithm respectively. After dividing by FCM algorithm the mirror, pillar and the ribbon on hat cannot be distinguished well. Detail parts such as hair and cap ear cannot be distinguished clearly. While these can be distinguished well by KWFCM.

Fig 2.a)

Fig 2.b)

Fig 2.c)

Fig 2.a) The primitive image Fig 2.b) The image after division by FCM algorithm Figure 2.c) The image after division by KWFCM algorithm

In order to reduce the computational complexity, we can approximate the fuzzy filtering using a signal Processing approach as shown in [10]. Moreover, another clever implementation strategy devised for median filter [13] is employed to greatly improve the fast filtering performance.

In Figure 3, we compare our technique to the Perona- Malik's anisotropic diffusion filter [1], the fuzzy vector median filter [7] and the Non-Local Means filter [15]. The fuzzy vector median filter [7] and the Non-Local Means filter [15] removes the noise in the degraded image, but the edges are as blurred as those in the degraded image. Our method removes the mixed noise a little better than the other three ones in [1], [7], [15].

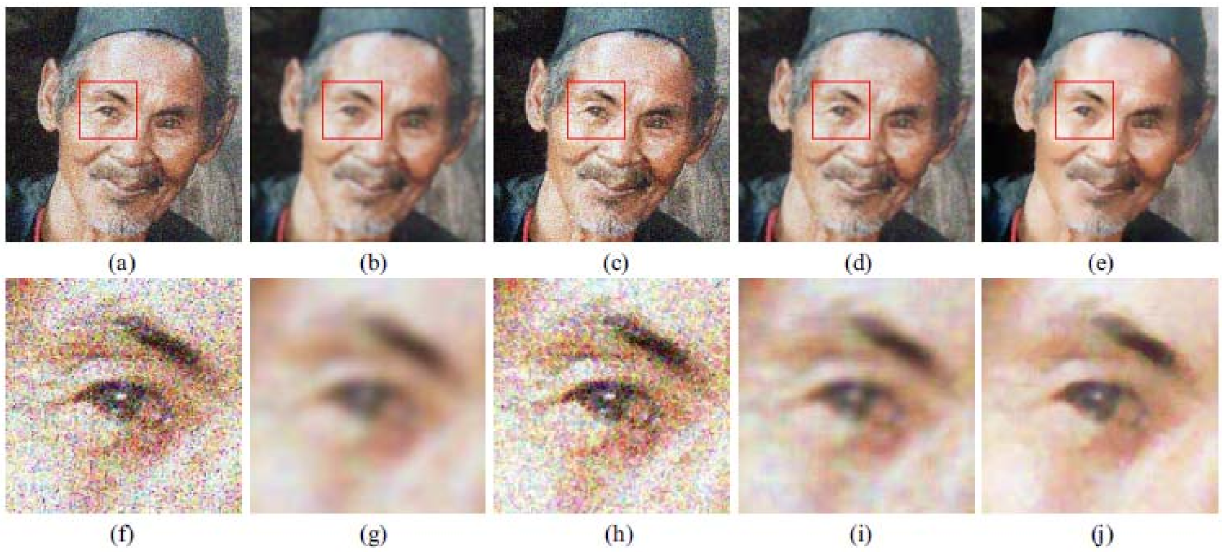

Figure 3. Denoising results with mixed noise by the Perona-Malik's anisotropic diffusion filter [1], the fuzzy vector median filter [7] and the Non-Local Means filter [15], compared to results produced with our FF-based approach. (a) images corrupted by mixed noise (10%); (b) results by the Perona-Malik's anisotropic diffusion filter [1]; (c) results by the fuzzy vector median filter [7]; (d) results by the Non-Local Means filter [15]; (e) our restored images; (f)-(j) the regions inside the red boxes in (a)-(e) are zoomed in.

4. Conclusion

In this paper, we propose the bilateral filtering using KW fuzzy c means(KWFCM) for image manipulations, based on the unified nonlinear diffusion techniques. Our fuzzy filtering consists of the standard bilateral filter and the estimation of the pixel values by the fuzzy median filter. We have applied our fuzzy filtering for image denoising with both the impulse and Gaussian random noises. Our method achieves better denoised results than the bilateral filter based approach in [2], [10], the Perona-Malik's anisotropic diffusion filter [1], the fuzzy vector median filter [7], and the Non-Local Means filter [15]. Further, the FF-based tone mapping of HDR images is developed, which does not introduce unpleasant visual halo artifacts.

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