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MEDIAN FILTER TECHNIQUES FOR REMOVAL OF DIFFERENT NOISES IN DIGITAL IMAGES

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Abstract: The existence of noise is one of the most frequent problems in many digital image processing applications. So for the removal of such impulse noise median based filter becomes widely used. The purpose of the filter is to remove noise from a signal that might occur through transmission of an image. This paper gives comparison of different median filter techniques such as weighted median filter, recursive median filter, iterative median filter, directional median filter, adaptive median filter and switching median filter.

Keywords: Different noises, Median filters

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INTRODUCTION

Digital images which are related to digital signals are normally corrupted by many types of noise, including impulse noise [1]. Impulse noise is a set of random pixels which has a very high contrast compared to the surroundings. So, even a small percentage of impulse noise distorts the image greatly compared to other noises [2-3]. Malfunctioning pixels in camera sensors, faulty memory locations in hardware, or transmission of the image in a noisy channel, are some of the common causes for impulse noise [4].

In image processing it is usually necessary to perform high degree of noise reduction in an image before performing higher-level processing steps, such as edge detection. In software, a smoothing filter is used to remove noise from an image. Each pixel is represented by three scalar values representing the red, green and blue chromatic intensities. At each pixel studied, a smoothing filter takes into account the surrounding pixels to design a move accurate version of this pixel. By taking neighboring pixels into considerations, extreme 'noisy' pixels can be replaced. However, outlier pixels may represent in corrupted fine details, which may be lost due to the smoothing process. The median filter [5] is a non-linear digital filtering technique , often used to remove noise from images or other signals. The idea is to examine a sample of the input and decide if it is representative of the signal. This is performed using a window consisting of an odd number of samples.

The values in the window are sorted into numerical order; the median value, the sample in the center of the window, is selected as the output. The oldest sample is discarded, a new sample acquired, and the calculation repeats.

2. DIFFERENT NOISES

In common use the word noise means unwanted sound or noise pollution. In electronics noise can refer to the electronic signal corresponding to acoustic noise (in an audio system) or the electronic signal corresponding to the (visual) noise commonly seen as 'snow' on a degraded television or video image. In signal processing or computing it can be considered data without meaning; that is, data that is not being used to transmit a signal, but is simply produced as an unwanted by-product of other activities. In Information Theory, however, noise is still considered to be information. In a broader sense, film grain or even advertisements in web pages can be considered noise.

Noise can block, distort, or change the meaning of a message in both human and electronic communication. In many of these areas, the special case of thermal noise arises, which sets a fundamental lower limit to what can be measured or signaled and is related to basic physical processes at the molecular level described by well known simple formulae.

1) Salt & Pepper: As the name suggests, this noise looks like salt and pepper. It gives the effect of "On and off" pixels.

2) Gaussian: This is Gaussian White Noise. It requires mean and variance as the additional inputs.

3) Poisson: Poisson noise is not an artificial noise. It is a type of noise which is added from the data instead of adding artificial noise to the data.

4) Speckle: It is a type of multiplicative noise. It is added to the image using the equation J=I + n*I, where n is uniformly distributed random noise with mean 0 and variance V.

Noise can generally be grouped in two classes:

1) Independent noise, and

2) Noise which is dependent on the image data.

Image independent noise can often be described by

an additive noise model, where the recorded image

f(i,j) is the sum of the true image s(i,j) and the noise

n(i,j):

$$f(i,j) = s(i,j)+n(i,j) \quad (1)$$

The noise n(i,j) is often zero-mean and described by

its variance . The impact of the noise on the image is often described by the signal to noise ratio (SNR),

which is given by

$$SNR = \frac{\sigma_s}{\sigma_n} = \sqrt{\frac{\sigma_f}{\sigma_n} - 1} \quad (2)$$

Where ${\sigma^2}_n$ and ${\sigma^2}_f$ are the variances of the true image and the recorded image, respectively. In many cases, additive noise is evenly distributed over the frequency domain (i.e. white noise), whereas an image contains mostly low frequency information. Hence, the noise is dominant for high frequencies and its effects can be reduced using some kind of low pass filter. This can be done either with a frequency filter or with a spatial filter. (Often a spatial filter is preferable, as it is computationally less expensive than a frequency filter.)

In the second case of data dependent noise, (e.g. arising when monochromatic radiation is scattered from a surface whose roughness is of the order of a wavelength, causing wave interference which results in image speckle), it can be possible to model noise with a multiplicative, or non-linear, model. These models are mathematically more complicated, hence, if possible, the noise is assumed to be data independent.

3. VARIOUS MEDIAN FILTERING TECHNIQUES

Much wider range of algorithms is provided to filter the digital images from the impulse noise. Here in this Survey paper we study various median filtering techniques to remove impulse noise.

A. Standard median filter (SMF)

The standard median filter [6] is a simple rank selection filter also called as median smoother, introduced by tukey in 1971 that attempts to remove impulse noise by changing the luminance value of the centre pixel of the filtering window with the median of the luminance values of the pixels contained within the window. Although the median filter is simple and provides a reasonable noise removal performance, it removes thin lines and blurs image details even at low noise densities. The filtered image S = {S(i,j)} from SMF can be defined by the following equation [3]:

$$S(i,j) = \text{Median}_{(k,l)\in W_{m,n}}\{D(i+k, j+l)\} \qquad (3)$$

Where $W_{m,n}$ is a sliding window of size $m\times n$ pixels cantered at coordinates (i, j). The median value is calculated by using equation (3) with $ns= m\times n$ although SMF can significantly reduce the level of corruption by impulse noise, uncorrupted pixel intensity values are also altered by SMF. This undesired situation happens because SMF does not differentiate between uncorrupted from corrupted pixels. Furthermore, SMF requires a large filter size if the corruption level is high. Yet, large filter of SMF will introduce a significant distortion into the image [7].

It is worth noting that equation (1) is normally using sorting algorithm such as quick-sort or bubble-sort to arrange the samples in increasing or decreasing order. Even though sorting algorithm can be easily implemented, sorting procedure requires long computational time when $W_{m,n}$ is a large filter because the number of samples (i.e. $n_s = m \times n$) is big. Thus, in order to avoid from using any direct sorting algorithm, the use of local histograms has been proposed for median value calculation. The time required to form local histogram can be reduced by using a method proposed by Huang et al. [8], where instead of updating $m \times n$samples, only $2m$ samples need to be updated in each sliding-iteration.

B. Weighted Median Filter (WMF)

Weighted median filter is one of the branch of median filter (WMF). It was first introduced by Justusson in 1981, and further elaborated by Brownrigg. The operations involved in WMF are similar to SMF, except that WMF has weight associated with each of its filter element. These weights correspond to the number of sample duplications for the calculation of median value. The filtered image $S = \{S(i, j)\}$ from WMF can be defined by the following equation :

$$S(i,j)=Median_{(k,l)\in W_{m,n}}\{W_{m,n}(k,l)\otimes D(i+k, j+l)\} \quad (4)$$

Where operator $\otimes$ indicates repetition operation. The median value is calculated using equation (3) with n_s is equal to the total of $W_{m,n}(k,l)$. Normally, the filter weight $W_{m,n}$ is set such that it will decrease when it is located away from the center of the filtering window. By doing so, it is expected that the filter will give more emphasis to the central pixel, and thus improve the noise suppression ability while maintaining image details [9]. However, the successfulness of weighted median filter in preserving image details is highly dependent on the weighting coefficients, and the nature of the input image itself. Unfortunately, in practical situations, it is difficult to find the suitable weighting coefficients for this filter, and this filter requires high computational time when the weights are large .

1. Central Weighted Median Filter (CWMF)

It is special type of median filter. CWM is a filtering technique in which filter gives more weight only to the central value of a window, and thus it is easier to design and implement than general WM filters [10].

2. Adaptive Weighted Median Filter (AWMF)

Adaptive weighted median filters (AWMF), which is an extension to WMF. By using a fixed filter size $W_{m,n}$, the weights of the filter will be adapted accordingly base on the noise content. This adaptation can be done in many ways, mostly based on the local statistics of the damaged image [11].

C. Directional Median Filter

Directional median filter, or also known as stick median filter, works by separating its 2-D filter into several 1-D filter components [12]. Each filter component or stick, presented as a straight line, corresponds to a certain direction or angle. For a window of size $m \times n$ pixels, there are $m+n-2$ sticks that will be used. The computed median values from these 1-D filters are then combined to obtain the final result. In [13], the output intensity is defined as:

$$S(i,j)=max\{Median(k,l) \in W\Theta \{D(i+k, j+l)\}\} \quad (5)$$

Where $W\Theta$ is the stick. Here, the output intensity is defined as the largest median value determined at each location.

D. Iterative Median Filter

Iterative method requires the same procedure to be repeated several times. In general, iterative median filter with *ni* iterations, requires *ni* -1 temporary images. Iteration procedure enables median filtering process to use smaller filter size and reduce the computational time, while maintaining local features or edges of the image. The number of iterations *ni* can be set by the user, or the iteration process stops when the output image converged (i.e. the current output image is equal to the previous output image). In practical, the number of iterations needed is dependent to the level of corruption and also the nature of the input image itself [14].

E. Recursive Median Filter

The recursive median (RM) filter is a modification of the SM filter defined in (1). RM filtering can extract signal roots better than SM filtering, and is useful alternative to SM filtering in some applications. In general, RM filters are implemented by modifying an SM filtering algorithm and, as a consequence, the implementation of RM filters is computationally and structurally more complex than that of SM filters [15].

F. Adaptive Median Filter

The Adaptive Median Filter is designed to eliminate the problems faced with the standard median filter. The basic difference between the two filters is that, in the Adaptive Median Filter, the size of the window surrounding each pixel is variable. This variation depends on the median of the pixels in the present window. If the median value is an impulse, then the size of the window is expanded.

Otherwise, further processing is done on the part of the image within the current window specifications. 'Processing' the image basically entails the following: The center pixel of the window is evaluated to verify whether it is an impulse or not. If it is an impulse, then the new value of that pixel in the filtered image will be the median value of the pixels in that window. If, however, the center pixel is not an impulse, then the value of the center pixel is retained in the filtered image. Thus, unless the pixel being considered is an impulse, the gray-scale value of the pixel in the filtered image is the same as that of the input image. Thus, the Adaptive Median Filter solves the dual purpose of removing the pulse noise from the image and reducing distortion in the image. Adaptive Median Filtering can handle the filtering operation of an image corrupted with impulse noise of probability greater than 0.2. This filter also smoothens out other types of noise, thus, giving a much better output image than the standard median filter.

G. Switching Median Filter

Nowadays, one of the popular median filtering approaches is switching median filter, or also known as decision based median filter. This approach has been used in recent works, such as [16]. Switching median filter tries to minimize the undesired alteration of uncorrupted pixels by the filter. Therefore, in order to overcome this problem, switching median filter checks each input pixel whether it has been corrupted by impulse noise or not. Then it changes only the intensity of noisy pixel candidates, while left the other pixels unchanged. Normally, switching median filter is built from two stages. The first stage is for noise detection, while the second stage is for noise cancellation. The output from the noise detection stage is a noise mask M. This mask is a binary mask. Noise detection procedure used by researchers are normally depending on the noise model been used. For fixed-valued impulse noise (i.e. salt-and-pepper noise), mostly the noise detection is done by thresholding the intensity values of the damaged image. Other popular noise detection methods include by checking the difference between intensity of the current pixel with its surrounding, inspecting the difference of the damaged image with its median filtered versions, or by applying some special filters. Next, mask **M** will be used in the noise cancellation stage, where only pixels with $M = 1$ are processed by the median filter. For the calculation of median, only "noise-free" pixels (i.e. pixels with $M = 0$) are taken as the sample.

4. SUMMARY

This paper surveys seven common median filtering techniques. Each technique has its own advantages, and disadvantages. From literature, we found that most of the recent median filtering based methods employ two or more than two of these framework in order to obtain an improved impulse noise cancellation.

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