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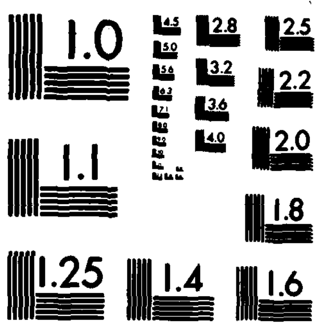

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NONLINEAR EDGE PRESERVING FILTERING TECHNIQUES FOR IMAGE ENHANCEMENT*

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ABSTRACT

Recently introduced generalizations of the median filter (namely the α-trimmed mean and modified trimmed mean filters) are reviewed and related to a class of nonlinear filters called selective averaging filters, and two new filters are defined. These filters are examined for performance on noise-corrupted images and shown to have good smoothing characteristics without edge smearing.

I. INTRODUCTION

The simple nonlinear action of the median filter allows it to generally preserve edges while suppressing impulsive noise components quite well. Median filtering, however, may fail to provide sufficient smoothing of non-impulsive noise components such as white Gaussian noise. Several new filters have recently been studied as generalizations of the median filter. Specifically, the <u>α-trimmed mean filter</u> (α-TM filter) [1-3] and the <u>modified trimmed mean filter</u> (MTM filter) [3] have been proposed as useful new nonlinear filters. The class of nonlinear filters called <u>selective averaging filters</u> [4], which includes the <u>K-nearest neighbor filter</u> (K-NN filter) [4,5], can be related to these generalized median filters. We will examine this relationship in Section II and from this relationship will be able to define two other new filters, the <u>median K-nearest neighbor filter</u> (MED K-NN filter) and the <u>modified nearest neighbor filter</u> (MNN filter). In Section III we will give results of experiments in which these filters are applied to noisy images.

All of the filters considered in this paper are local image enhancement techniques in which each pixel is replaced by a value obtained through an operation performed on a neighborhood W of the pixel. The size of a window or neighborhood is the total number of pixel locations in it. We will generally be interested in odd window sizes which we will write as 2N+1 for an integer N. The output $y_{k,l}$ of an α-TM filter of window size 2N+1 at pixel location (k,l) for an input image $\{x_{k,l}\}$ is the average value of pixels remaining in the window after the $T = [\alpha(2N+1)]$ largest and smallest pixels are discarded, with α being some parameter constrained by $0 \le \alpha \le 0.5$. The MTM filter first determines the sample median $m_{k,l}$ of pixels within the window centered on any pixel location (k,l), and then chooses an interval $[m_{k,l}-q, m_{k,l}+q]$ using some pre-selected constant q. Within the window, data samples outside this range are discarded and the average value of the rest of the data is used as the output. MTM filtering can be thought of as a modification of α-TM filtering [3]. Note that the number of values used in averaging is not fixed <u>a priori</u> in MTM filtering, while it is fixed as 2(N-T)+1 in α-TM filtering. The MTM filter is able to reject impulsive noise components because for each output it starts by obtaining the median value inside the corresponding window. Note that the MTM filter also treats its ordered data within a window in a non-symmetric way depending on the data.

The window sizes of α-TM and MTM filters are constrained as in median filtering. If a narrow pulse of the original image, composed of I pixels is to be preserved, then the maximum window size, allowed is 2I-1 in the noise-free case. To overcome this difficulty a double-window (DW) variation of the MTM filter has been introduced [3]. In the double-window MTM filter (DW MTM filter) windows of size 2N+1 and 2L+1, with L > N, are centered at (k,l). First the sample median $m_{k,l}$ is computed from the small window of size 2N+1. For some positive number q an interval $[m_{k,l}-q, m_{k,l}+q]$ is chosen. Then the mean of points lying within the interval $[m_{k,l}-q, m_{k,l}+q]$ among the samples in the larger window of size 2L+1 is computed as the output. The condition concerning preservation of a narrow pulse composed of I connected pixels, namely, $2N+1 \le 2I-1$, is a necessary but not sufficient condition in the two-dimensional case (it is sufficient and necessary in one dimension). In general we can say that a narrow pulse composed of I pixels will always be preserved by median filtering of window size $2N+1 \le 2I-1$ if at least N+1 pixels of the narrow pulse are included in the window whenever the subject pixel (center of the window) comes from the narrow pulse.

II. RELATIONSHIP OF GENERALIZED MEDIAN FILTERS TO SELECTIVE AVERAGING FILTERS

Selective averaging [4] refers to a class of local image enhancement techniques which are designed specifically to not average across edges, or lines. At each pixel, called the subject pixel, every value in its window is examined.

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Then the general idea is that only those pixels coming from the same region (for example, same side of an edge) as the subject pixel are averaged and the rest are discarded. Note that the generalized median filters, especially the α-TM and MTM filters, follow the same general policy except that they average pixel values close to the median pixel. In particular, one selective averaging technique called the K-nearest neighbor filter (K-NN filter) [4,5] will now be shown to be closely related to α-TM and MTM filters.

Two versions of a K-NN filter may be defined. In the first version ($K\text{-}NN_1$), in each window the filter averages a fixed number K of values closest to the subject pixel, including the pixel itself, where K is an integer less than or equal to the window size 2N+1. The output is then this averaged value. This $K\text{-}NN_1$ filter is similar to the α-TM filter in the sense that it averages a fixed number of selected values inside each window. Thus in non-impulsive noise suppression the $K\text{-}NN_1$ and the α-TM filters can be designed to have similar performances (by choosing $K = 2(N-T)+1$). However, impulsive noise components cannot be suppressed effectively, in general, by averaging the values within a window which are close to the value of the center pixel. This is because the center pixel itself may have been corrupted by an impulsive noise component. Generalized median filters can suppress impulsive noise because they average values close to the median. On the other hand, the $K\text{-}NN_1$ filter has a non-symmetric data-dependent smoothing property as in MTM filtering. It always averages K consecutive pixel values from amongst the ordered set, but the location of these values in the ordered set is not fixed. Thus the $K\text{-}NN_1$ filter can be more effective than the α-TM filter in edge preservation for properly chosen K; for example, when a 3 x 3 symmetric square window is used the $K\text{-}NN_1$ filter with $K \leq 6$ will preserve a noise-free step edge with a horizontal, vertical or diagonal orientation. In addition, iterated use of the $K\text{-}NN_1$ filter can result in impulsive noise suppression, because at each iteration the value of an impulsive component is reduced and non-impulsive components are not influenced by the presence of impulsive components.

In $K\text{-}NN_1$ filtering the window size can be chosen more freely because, for a fixed K, different window sizes generally do not result in very different performances as long as they are all reasonably big. We can observe this explicitly in the one-dimensional case, in which $K \leq N+1$ is the necessary and sufficient condition for the preservation of noise-free step edges, and both $K \leq N+1$ and $K \leq I$ are the necessary and sufficient conditions for the preservation of a noise-free narrow pulse of duration I; note that such a narrow pulse can generally be written as

$$x_k = \begin{cases} 0 \quad , & k < j \\ H_1 & j \leq k < j+I \\ H_2 & j+I \leq k \end{cases} \qquad (1)$$

where j is an integer and $H_1 \neq 0$, $H_2 \neq H_1$. Thus a large window size can be chosen without distorting narrow pulses, although the degree of non-impulsive noise suppression is not changed by increasing window size for a fixed K. In the two-dimensional case the conditions $K \leq N+1$ and $K \leq I$ have to be modified, depending on the shapes of the window, the narrow pulses and edges. For instance, when a symmetric square window of size 2N+1 is used, horizontal or vertical edges will be preserved by choosing $K \leq \sqrt{2N+1}\,(\sqrt{2N+1}+1)/2$. Concerning the preservation of two-dimensional narrow pulses, a statement similar to the one mentioned at the end of the previous section can be made; a narrow pulse composed of I pixels will be preserved by K-NN filtering with $K \leq I$ if all of the pixels in the narrow pulse are included in the window whenever the subject pixel is part of the narrow pulse.

We should note that in [4,5] a filter has been defined (which we will describe as the $K\text{-}NN_2$ filter) in which the subject pixel is excluded from the averaging. In other words, the window W does not include the subject pixel. Use of this type of window for the K-NN filter may have an advantage in that the filter can suppress isolated impulsive noise components. However, for both K-NN filters impulsive noise suppression can be achieved by repeated filtering.

The α-TM filter averages a fixed number of values symmetrically in a neighborhood of the median, and is a direct extension of a median filter. The K-NN filter averages a fixed number of values in a neighborhood of the subject pixel, which results in non-symmetric treatment of the ordered data, and may be viewed as an extension of an identity filter. This comparison brings up the possibility of a symmetric K-NN filter averaging a fixed number of values as a direct extension of the identity filter and a counterpart of the α-TM extension of the median filter. For instance, in the one-dimensional case, when the subject pixel is x_k a symmetric $K\text{-}NN_1$ filter may be defined to select (K-1)/2 samples from each of the sets $\{x_i | k-N \leq i < k\}$ and $\{x_i | k < i \leq k+N\}$, for an odd K. However, this extension of the identity filter can be expected to neither preserve edges well nor suppress impulsive noise components and will not be considered further. On the other hand, one can also think of a non-symmetric α-TM filter which averages a fixed number of values in a neighborhood of the median as in α-TM filtering, but with possibly a different number of values selected from either side of the median. This leads to a filter which averages K pixels whose gray levels are closest to the median amongst the gray levels in any window; we will refer to it as the median K-NN filter. The window sizes of the median K-NN filter are restricted as in median filtering, while K is chosen as in K-NN filtering.

MTM filtering, in which a variable number of values are averaged non-symmetrically in a neighborhood of the median, can be thought of as a modification of median $K\text{-}NN_1$ filters. The K-NN filters can be modified to average a variable number of samples non-symmetrically in the same way that the median $K\text{-}NN_1$ filter can be modified to give the MTM filter. This leads us to filters which will be called the modified nearest neighbor filters (MNN filters). The MNN filters average values lying within some interval $[x_k-q,\ x_k+q]$ amongst the values in their window, where x_k is the gray level of the subject pixel.

The MNN_1 filter cannot suppress impulsive noise components effectively even with iterated use because it averages values close to the subject pixel value in any window; however, it can smooth non-impulsive noise without blurring. The behavior of the MNN_1 filter varies from that of the identity filter (no filtering) when the subject pixel has been corrupted by an impulsive noise to that of the running mean filter when the subject pixel is located in a slowly varying portion of the image, for a properly chosen q.

We have noted, in Section II, that a DW MTM filter allows one to achieve more smoothing without severe loss of narrow pulses in an image. Increasing the window size of an MTM filter directly does not allow this advantage to be obtained. In MNN_1 filtering, increasing the window size does allow more smoothing without loss of narrow pulses for a properly chosen q; of course, MNN_1 filtering does not give impulsive noise rejection. For instance, the one-dimensional noise-free narrow pulse of (1) will be preserved for any window size as long as

$$q < \min\{H_1,\ H_2,\ |H_1-H_2|\}. \qquad (2)$$

If only

$$q < \min\{H_1,\ H_2\} \qquad (3)$$

holds the pulse is also preserved, as long as the window size is not larger than 2I+1. Note that the DW MTM filter also preserves the pulse (1), as long as the condition (2) holds and the small window size is not larger than 2I-1, for arbitrarily large window size. If only (3) holds than the pulse (1) is also preserved in DW MTM filtering if the large window size is no larger than *2I+1*

It is interesting to note that the MTM and MNN_1 filters can be represented as a weighted average of the form

$$y_{k,\ell} = \frac{\sum\sum_{W} a_{r,s}\, x_{k+r,\ell+s}}{\sum\sum_{W} a_{r,s}} \qquad (4)$$

When

$$a_{r,s} = \begin{cases} 1, & |x_{k+r,\ell+s} - m_{k,\ell}| \le q \\ 0, & \text{otherwise} \end{cases} \qquad (5)$$

we get the MTM filter. The MNN_1 filter is obtained by replacing $m_{k,\ell}$ in (5) with $x_{k,\ell}$. The DW MTM filter can also be obtained by using the large window as W in (4) and by using $m_{k,\ell}$ from the small window in (5).

III. EXPERIMENTS

In this section we give some results of the application of the above nonlinear filters in image processing. The original image under consideration consisted of 100 x 100 pixel values with eight bits of resolution per pixel. It was a geometric image of flat portions with gray levels either 100 or 150, and a sinusoidal part whose maximum amplitude was 150 and minimum amplitude was 100. The height of edges was 50 except for the lower diagonal one (see photographs on the next page) whose height was 35. Each cross-shaped narrow pulse was composed of 12 pixels having a constant gray level of 150. Two types of noise were added to the original image; zero-mean white Gaussian noise with standard deviation 10 and 100 impulses which occurred at random positions, with gray levels 250. The filters discussed so far, with a 3 x 3 square window, were applied to the noisy image and this application was iterated three times. (The notation 3I in the photographs stands for "3 iterations"). In DW MTM filtering 3 x 3 and 7 x 7 square windows were used. The MNN_1 filter was also used with a 7 x 7 square window on 3 x 3 square-window median filtered data. The parameter K for the K-NN_1 and median K-NN_1 filter was chose to be 6 and the parameter q for the MTM, DW MTM and MNN_1 filters was chosen to be 30 (i.e. $q \approx H-2\sigma$, except for the lower diagonal edge).

The MTM filter after three iterations is seen to be better in noise suppression than the iterated median, median K-NN_1 and K-NN_1 filters, which give a more mottled appearance. The results of the DW MTM filter and the median filter followed by the MNN_1 filter are seen to be quite similar and better than all the other results.

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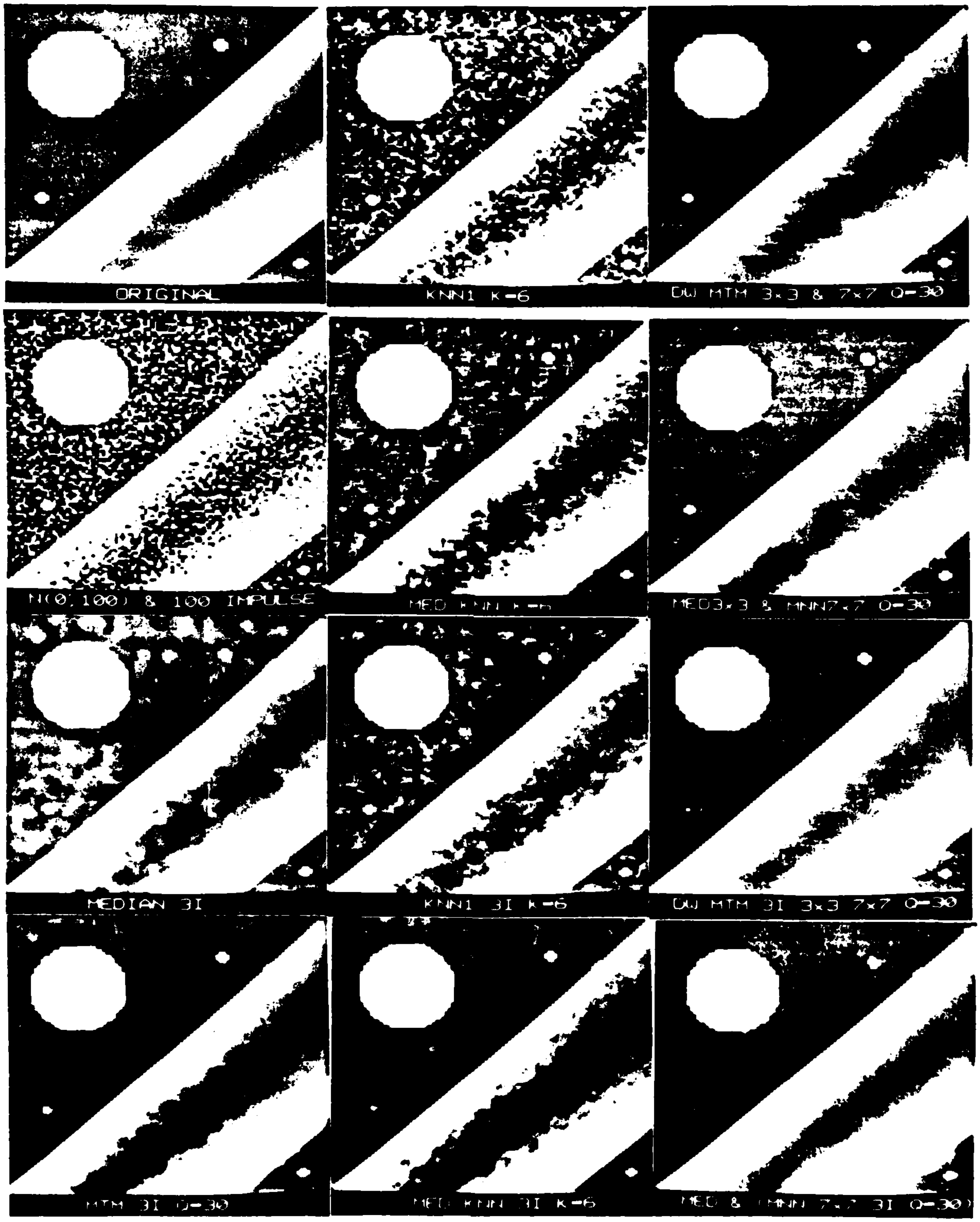
ORIGINAL
KNN1 K=6
DW MTM 3x3 & 7x7 Q=30
N(0,100) & 100 IMPULSE
MED KNN K=6
MED3x3 & MNN7x7 Q=30
MEDIAN 3I
KNN1 3I K=6
DW MTM 3I 3x3 7x7 Q=30
MTM 3I Q=30
MED KNN 3I K=6
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