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ADAPTIVE NON LINEAR DEBLURRING TECHNIQUE: A NEW IMAGE ENHANCEMENT TECHNIQUE

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Abstract
This work deals with the issue of developing new automatic image enhancement techniques for use in wireless and mobile applications. This research intends to improve the efficacy of intensity changes in picture enhancement. To do this, we provide a novel method for improving the photos that is based on an estimation of the cumulative distribution for the brightness scale's sub-ranges. By using parameter-free intensity transforming, the author suggests a novel image enhancing strategy to illustrate the potential of this method. The suggested method enables efficient contrast augmentation of complicated images without the emergence of undesired defects. The efficiency of the suggested technique is demonstrated by experimental study employing no-reference metrics and professional estimates of picture contrast.
Keywords: Enhancement Technique,, wireless and mobile applications, intensity changes, estimation and cumulative distribution.

I. INTRODUCTION

THE application of fuzzy techniques in image processing ia promising research field Fuzzy techniques have al-ready been applied in several domains of image processing (e.g., filtering, interpolation , and morphology , and have numerous practical applications (e.g., in industrial and medical image processing [5], [6]).In this paper, we will focus on fuzzy techniques for image filtering. Already several fuzzy filters for noise reduction have been developed, e.g., the well known FIRE-filter from, the weighted fuzzy mean filter from and,and the iterative fuzzy control based filter from [12]. Most fuzzy techniques in image noise reduction mainly dealwith fat-tailed noise like impulse noise. These fuzzy filters are ableto outperform rank-order filter schemes (such as the median filter). Nevertheless, most fuzzy techniques are not specifically designed for Gaussian(-like) noise or do not produce convincing results when applied to handle this type of noise.

Therefore, this paper presents a new technique for filteringnarrow-tailed and medium narrow-tailed noise by a fuzzyfilter. Two important features are presented: first, the filterestimates a "fuzzy derivative" in order to be less sensitive tolocal variations due to image structures such as edges; second,the membership functions are adapted accordingly to the noiselevel to perform "fuzzy smoothing."The construction of the fuzzy filter is explained in Section II.For each pixel that is processed, the first stage computes a fuzzyderivative. Second, a set of 16 fuzzy rules is fired to determinea correction term. These rules make use of the fuzzy derivativeas input. Fuzzy sets are employed to represent the properties, , and . While the membership func-tions for and are fixed, the membershipfunction for is adapted after each iteration. The adapta-tion scheme is extensively explained in Section III and can becombined with a statistical model for the noise. In Section IV,we present several experimental results. These results are dis-cussed in detail, and are compared to those obtained by otherfilters. Some final conclusions are drawn in Section V.

II. What is Fuzzy Filter:

The general idea behind the filter is to average a pixel using other pixel values from its neighborhood, but simultaneously to take care of important image structures such as edges. 1 The main concern of the proposed filter is to distinguish between local variations due to noise and due to image structure.In order to accomplish this, for each pixel we derive a value that expresses the degree in which the derivative in a certain direction is small. Such a value is derived for each direction corresponding to the neighboring pixels of the processed pixel by a fuzzy rule (Section II-A).The further construction of the filter is then based on the ob-serration that a small fuzzy derivative most likely is caused by noise, while a large fuzzy derivative most likely is caused by an edge in the image. Consequently, for each direction we will apply two fuzzy rules that take this observation into account(and thus distinguish between local variations due to noise anddue to image structure), and that determine the contribution of the neighboring pixel values. The result of these rules (16 in total) is desfuzzified and a "correction term" is obtained for the processed pixel value (Section II).a significant fuzzy derivative, on the other hand, is probably the result of an image edge.In order to distinguish between local fluctuations caused by noise and those caused by image structure, we will apply two fuzzy rules for each direction that take into account this observation and calculate the contribution of the nearby pixel values. A "correction term" is derived for the processed pixel value when the outcome of these rules (16 in total) is defuzzified (Section II-)

III: Estimation of fuzzy derivatives

Estimating derivatives and filtering can be viewed as a "chicken-and-egg" scenario in which we require filtering to locate the edges while we desire a good indication of the edges for filtering.Other fuzzy filters, like the smoothing fuzzy control based filter [12], also take care of edges, but in our technique, we start by looking for the edges rather than doing so concurrently with the noise filtering.Through the use of fuzzy rules, we attempt to produce a reliable approximation.Take a look at the area around a pixel in Fig. 1. (a).The difference between the pixel at and its neighbour in the direction is what is known as a simple derivative at the central pixel position in the direction.

Next, this derivative value is represented as The fuzzy derivative's basic tenet is based on the observation that follows.Consider an edge that travels in the direction of a pixel and passes through the area nearby.The derivative value will be high, but it's also reasonable to anticipate that surrounding pixels' derivative values perpendicular to the edge's direction will also be high.We can compute the values, and, for instance, in the -direction [see Fig. 1(b)].

The goal is to eliminate the impact of a single derivative value that, as a result of noise, turns out to be high.Therefore, it is reasonable to assume that there is no edge in the considered direction if two out of the three derivative values are tiny.When developing the fuzzy rule to calculate, we shall take this observation into consideration.

the values of the fuzzy derivation.We list the pixels we employ to calculate the fuzzy derivative for each direction in Table I.

The sets in column 3 determine which pixels are taken into consideration with respect to the central pixel; each direction (column 1) corresponds to a fixed position (column 2);

In order to determine the value that represents how small the fuzzy derivative is in a certain direction, tset .The minimum is used to represent the AND operator in these rules, and the maximum is used to represent the OR operator.

Since the fuzzy smoothing stage uses the membership degrees directly, a defuzzification is not required.Several basic derivatives surrounding the pixel are combined to create the fuzzy derivative's robustness, and the parameter is made adaptive.

Later, it will be addressed which is the best.

IV Fuzzy Blending:

We employ a pair of fuzzy rules for each direction to calculate the correction term for the processed pixel value.

According to the regulations, the corrective term can and will be calculated using the (crisp) derivative value in the direction in which it is presumed there is no edge.

The fuzzy derivative value can be used to actualize the edge assumption in the first section, but in order to implement the filtering in the second half, we must distinguish between positive and negative values.For illustration, let's think about the direction.
We apply the following two rules and determine their veracity using the valueand:Weemploy linear membership functions .Once more, we add the AND and OR operators by setting the minimum and maximum values, respectively. You can carry out this for every direction. Defuzzification is the last process in the fuzzy filter's computation.We are looking for a correction term that may be added to the location-related pixel value.Consequently, the rules' accuracy and authentication is must.

Selecting an adaptive threshold:

We prefer to apply the filter iteratively rather than using wider windows to get better results for heavy noise.Each member's function's shape is customised.iteration based on an estimation of the noise's (remaining) volume. In order to estimate the noise density, the method presupposes that a portion of the image can be regarded as homogeneous.
The image is first divided into small, nonoverlapping parts. We determine a preliminary estimate of the homogeneity of each block by taking into account its maximum and minimum pixel values This metric is frequently applied while processing blurry images . A histogram of the homogeneity values is then displayed . The most homogeneous blocks are found. We presume that this percentile represents a measurement of how uniform the image's "average" noise is. We shall demonstrate that there is a linear relationship between the homogeneity and the standard deviation using a statistical model for the noise distribution.
Assume that the noise samples,, and have a probability density function (PDF) and cumulative density function (CDF) that are independently and identically distributed. The maximum and lowest of the samples are scaled in the same way since a change in the standard deviation rescales the PDF. By doing so, a linear link between homogeneity and standard deviation is established. Another way to obtain this is formally. We consider the variance to be and the expectation value to be both zero. If we use a to scale the PDF,
of the noise samples,, and are independently and identically distributed. Since a change in the standard deviation rescales the PDF, the highest and lowest sample values are scaled similarly. This establishes a linear relationship between homogeneity and standard deviation. Formally obtaining this is another option. We take into account both the variance and the expectation value. After introducing Gaussian noise of varying intensities to grayscale test images (8-bit), the suggested filter is applied. Such atechnique enables us to assess and contrast the filtered picture. The normalised histogram of the homogeneity of the "cameraman" is shown in Fig. 5 for both the original image and the image that has been distorted by

various noise levels, i.e.,, and. The estimations for the noise levels are, in accordance with the 20% percentile and (8), 5.2, 9.4, and 17.7. Our filter is implemented for these noise levels using various values for the amplification factor, specifically. We calculated the mean squared error (MSE) between the original image and the filtered image in order to assess the outcomes.

A plot of the MSE as a function of the added noise iterations with and is shown in Figs. 6 and 7.Observe that one iteration is sufficient to effectively reduce noise at low noise levels . A low score The estimations for the noise levels are, in accordance with the 20% percentile and (8), 5.2, 9.4, and 17.7. Our filter is implemented for these noise levels using various values for the amplification factor, specifically. We calculated the mean squared error (MSE) between the original image and the filtered image in order to assess the outcomes.

A plot of the MSE as a function of the added noise iterations with and is shown in Figs. .

Observe that one iteration is sufficient to effectively reduce noise at low noise levels (Fig. 6). Also, outcomes are better when the amplication factor is low. The MSE of "cameraman" unexpectedly rises with the number of iterations, primarily because the image content, such as the very tall grass a kin to o noise and is filtered more and more. This increase is absent for other images, such as "boats." As a result, photos with fine textures and low noise levels should be handled cautiously.

The results of "cameraman" are substantially more consistent at high noise levels (Fig. 7). It takes only a few (3–4) iterations to effectively reduce noise. Additionally, a slightly larger value of produces better outcomes.

The parameter for the "boats" test image is shown in Fig.s .

We anticipate that this curve will flatten out when more iterations are performed because it depends on an estimate of the remaining noise level. We might use the estimate as a stop criterion as based on an estimation for the "natural" or "acceptable" quantity of noise (depending on the application). as a stop requirement once it drops low enough. Another potential stop criterion is when there has been a minimal change from the previous iteration.

The parameter has an impact on amount of noise on the image.

After introducing Gaussian noise of varying intensities to grayscale test images (8-bit), the suggested filter is applied. This method enables us to assess and compare the filtered image.

The normalised histogram of the homogeneity of the "cameraman" is shown in Fig. for both the original image and the image that has been distorted by various noise levels, i.e.,, and. The estimations for the noise levels are, in accordance with the 20% percentile and , 5.2, 9.4, and 17.7. Our filter is implemented for these noise levels using various values for the amplification factor, specifically. We calculated the mean squared error (MSE) between the original image and the filtered image in order to assess the outcomes.

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. The estimations for the noise levels are, respectively, 5.2, 9.4, and 17.7 using the 20% percentile and (8). Different values for the amplification factor, namely, are used to apply our filter to these noise levels. In order to assess the outcomes, we calculated the mean squared error (MSE) between the unfiltered and filtered images.

A plot of the MSE as a function of the multiplicity of iterations for additional noise with and is shown in Figs. 6 and 7.

One cycle is sufficient to effectively remove noise at low noise levels (Fig. 6), as can be shown. The best outcomes are also produced by low amplication factors. Surprisingly, the MSE of "cameraman" grows with the number of iterations. This is mostly because the image information, such as how tall the grass. In other words, the grass becomes increasingly filtered and is quite close to noise. This increase is absent for other images, such as "boats." As a result, photos with fine textures and low noise levels should be handled cautiously.

The results of "cameraman" are substantially more consistent at high noise levels (Fig. 7). It takes only a few (3–4) iterations to effectively reduce noise. Additionally, a slightly larger value of produces better outcomes.

The parameter for the "boats" test image is shown in Fig. .

We anticipate that this curve will flatten out when more iterations are performed because it depends on an estimate of the remaining noise level. We might utilise the estimation of the "natural" or "acceptable" quantity of noise based on an estimation for the application. as a stop requirement once it drops low enough. Another potential stop criterion is when there has been a minimal change from the previous iteration.

The setting has an impact on how much smoothing the filter applies. Considering what we've seen with the MSE-Figure displays the normalized histogram of the homogeneity of the "cameraman" for both the original image and the image that has been contaminated with various amounts of noise, i.e.,, and. The estimations for the noise levels are, in accordance with the 20% percentile and (8), 5.2, 9.4, and 17.7. Our filter is implemented for these noise levels using various values for the amplification factor, specifically. We calculated the mean squared error (MSE) between the original image and the filtered image in order to assess the outcomes.

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Observe that one iteration is sufficient to effectively reduce noise at low noise levels . Also, outcomes are better when the amplication factor is low. The MSE of "cameraman" unexpectedly rises with the number of iterations, primarily because the image content, such as the very tall grass.

The estimate could also be used to determine curves: A greater value of is associated with a higher noise level, while a lower noise a lower value of corresponds to level. Additionally, we evaluated the performance of our fuzzy filter in comparison to a number of other filtering methods, including the mean filter, the adaptive Wiener filter , the fuzzy median (FM) , the adaptive weighted fuzzy mean (AWFM1 and AWFM2) , the iterative fuzzy filter (IFC), the modified iterative fuzzy filter (MIFC), and the extended iterative fuzzy filter (EIFC) . The findings are listed in Table II.

The results between "cameraman" and "boats" are very different. The proposed filter performs quite well for "cameraman."

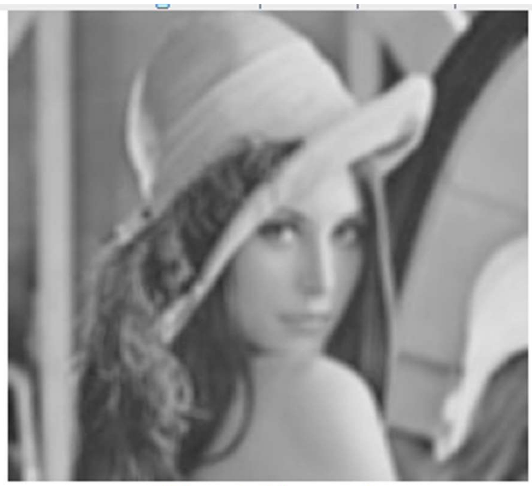
Filter is able to keep even the smallest elements (such the fine ropes) intact. On the other hand, the suggested filter produces a more "natural" image without the adaptive Wiener filter's "patchy look."

Finally, we would want to demonstrate a real-world use for the fuzzy filter. This picture restoration method could be used to improve satellite photographs in particular. Of course, it is impossible to determine a numerical indicator of how "excellent" the image is because the original image is already distorted by noise.

The original image and the outcomes of fuzzy filtering with various parameters are shown in fig. One may favour lighter or heavier filtering depending on the application (such as visual inspection or segmentation) (by choosing correspondingly). Finally, we would want to demonstrate a real-world use for the fuzzy filter. This picture restoration method could be used to improve satellite photographs in particular. Of course, it is impossible to determine a numerical indicator of how "excellent" the image is because the original image is already distorted by noise.

The original image and the outcomes of fuzzy filtering with various parameters are shown in figs. One may favour lighter or heavier filtering depending on the application (such as visual inspection or segmentation) (by choosing correspondingly).

Original Image



Distorted image 1

Conclusion

The new fuzzy filter for additive noise reduction was suggested in this research. Its primary characteristic is the use of a fuzzy derivative estimator to discern between local fluctuations caused by noise and those caused by picture structures. Fuzzy rules are activated to take into account every angle surrounding the processed pixel. The membership functions' shape is also modified based on how much noise is still there after each cycle. The new filter's and a straightforward stop criterion's viability is demonstrated by experimental data. The fuzzy filter can compete with cutting-edge filter approaches for noise reduction despite its relative simplicity and uncomplicated fuzzy operator implementation. Visual observation withis quick hardware implementation and adequately basic in implementation.

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