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MIXED NOISE REMOVAL BY WEIGHTED ENCODING WITH SPARSE NONLOCAL REGULARIZATION

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ABSTRACT:

During image acquisition and/or transmission, noise will be more or less introduced. Denoising (or noise removal) is a fundamental problem in image processing, aiming to estimate the original image from its noise corrupted observation while preserving as much as possible the image edges, textures and fine scale details. Mixed noise removal from natural images is a challenging task since the noise distribution usually does not have a parametric model and has a heavy tail. The prior knowledge of noise distribution plays an important role in noise removal. One typical kind of mixed noise is additive white Gaussian noise (AWGN) coupled with impulse noise (IN). Many mixed noise removal methods are detection based methods. They first detect the locations of impulse noise pixels and then remove the mixed noise is strong.

Here, we propose a simple yet effective method, namely Weighted Encoding for Mixed Noise Removal (WEMNR), for mixed noise removal. In WEMNR, there is not an explicit step of impulse pixel detection; instead, soft impulse pixel detection via weighted encoding is used to deal with IN and AWGN simultaneously. Meanwhile, the image sparsity prior and nonlocal self similarity prior are integrated into a regularization term and introduced into the variational encoding framework. Experimental results show that the proposed WEMNR method achieves leading mixed noise removal performance in terms of both quantitative measures and visual quality.

INTRODUCTION:

DURING image acquisition and/or transmission, noise will be more or less introduced. Denoising (or noise removal) is a fundamental problem in image processing, aiming to estimate the original image from its noise-corrupted observation while preserving as much as possible the image edges, textures and fine scale details. The prior knowledge of noise distribution plays an important role in noise removal. Two types of commonly encountered noise are additive white Gaussian noise (AWGN) and impulse noise (IN).

Objective:

Aim is to estimate the original image from its noise corrupted observation while preserving the image edges, textures and fine scale details.

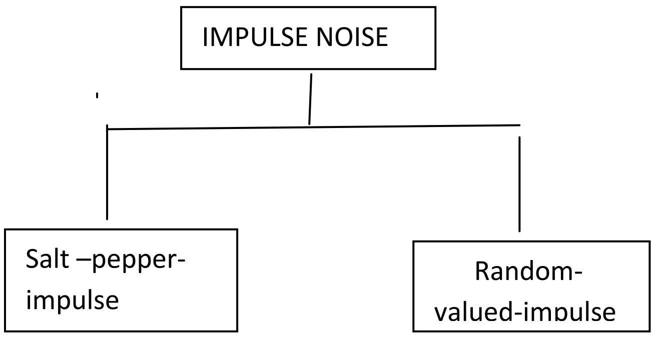
MIXED NOISE IN IMAGES:

It is a combination of both AWGN +IN.

AWGN: Initially Gaussian filter, Bilateral filter are used to remove AWGN.AWGN is the most widely studied noise model in image de-noising literature. At each pixel of an image corrupted by AWGN, a value independently sampled from a zero-mean Gaussian distribution is added to the pixel gray level. Traditional linear filtering methods such as Gaussian filtering can smooth noise efficiently but they will over-smooth the image edges at the same time. To solve this problem, nonlinear filtering methods have been developed. The well-known bilateral filter.

IMPULSE NOISE (IN):

Weighted median filter, centre-weighted median filter and the multistate median filter are used initially to remove IN. But we are using Adaptive Median Filter (AMF) to remove impulse noise (IN).



BLOCK DIAGRAM:

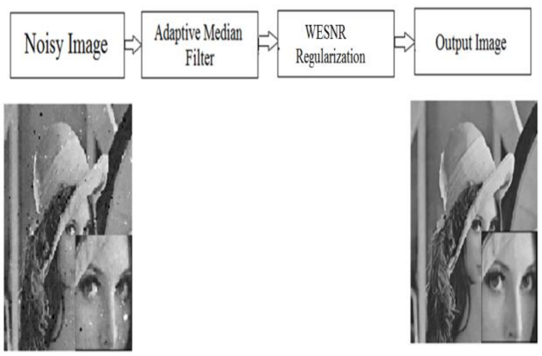
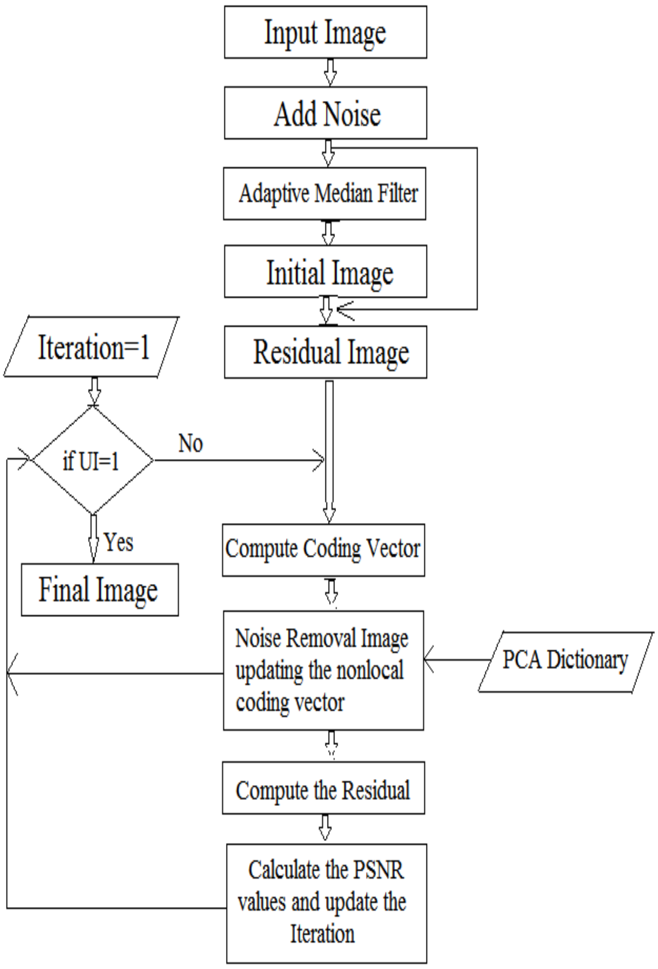


Fig 1:

FLOW CHART:



WESNR Algorithm:

1. Start
2. Load original image
3. Go to impulse noise
4. Go to Adpmedft
5. Go to WESNR Regularization
6. Display PSNR
7. End

Impulse Noise Algorithm:

Initialize ND=0.2, NT=0

- if NT =0==Salt and pepper noise else.
- NT =1==Random valued impulse noise.

RESULT:

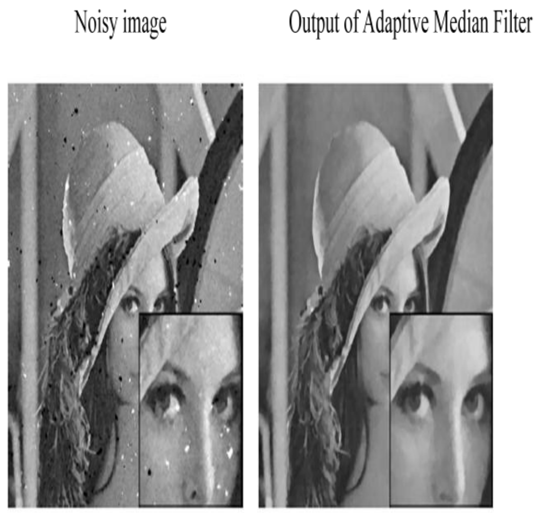


Fig 2:

APPLICATIONS:

- MEDICAL
- MILITARY
- INDUSTRIAL
- TRAFFIC

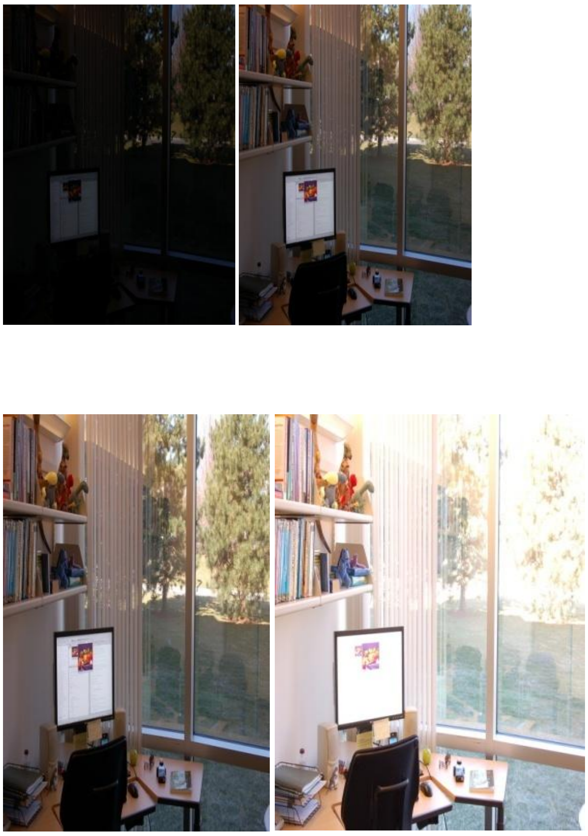


Fig 3:

Conclusion:

- We proposed a novel model for mixed noise removal namely Weighted Encoding with Sparse Nonlocal Regularization (WESNR).
- Additive white Gaussian noise mixed with impulse noise is much more irregular than Gaussian noise.
- AWGN is removed by using Non local Regularization method and IN is removed by using Adaptive Median Filter These methods are implemented by using MATLAB.

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