MIXED NOISE REMOVAL BY WEIGHTED ENCODING WITH SPARSE NONLOCAL REGULARIZATION

ABSTRACT

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. 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 IN pixels and then remove the mixed noise. However, such methods tend to generate many artifacts when the mixed noise is strong. In this paper, we propose a simple yet effective method, namely weighted encoding with sparse nonlocal regularization (WESNR), for mixed noise removal. In WESNR, 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 WESNR method achieves leading mixed noise removal performance in terms of both quantitative measures and visual quality

EXISTING SYSTEM

Existing mixed noise removal methods are detection based methods and they involve two sequential steps, i.e., first detect the IN pixels and then remove the noise. Such a two-phase strategy will become less effective when the AWGN or IN is strong. In this paper, we propose a simple yet effective encoding based method for mixed noise removal, namely weighted encoding with sparse nonlocal regularization (WESNR). There is no explicit impulse pixel detection in WESNR, and we encode each noise-corrupted patch over a pre-learned dictionary to remove the IN and AWGN simultaneously in a soft impulse pixel detection manner. The major difficulty of IN and AWGN mixed noise removal lies in the complex distribution of mixed noise, which has a heavy tail and cannot be readily characterized by a parametric model. The conventional l2-norm data fidelity term, which is well suited to characterize the Gaussian distributed data fitting residual, is not suitable to suppress the mixed noise with complex non-Gaussian distribution. In WESNR, the mixed noise is suppressed by weighting the encoding residual so that the final encoding residual will tend to follow Gaussian distribution. The weighted encoding and sparse nonlocal regularization are unified into a variational framework, which is easy to minimize. Extensive experiments are conducted to validate the proposed WESNR in comparison with state-of-the-art mixed noise removal methods.

DISADVANTAGES

- The Complexity was very high
- Does not provide the stability of weighted encoding

PROPOSED SYSTEM

We presented a novel model for mixed noise removal, namely weighted encoding with sparse nonlocal regularization (WESNR). The distribution of mixed noise, e.g., additive white Gaussian noise mixed with impulse noise, is much more irregular than Gaussian noise alone, and often has a heavy tail. To address this difficulty, we adopted the weighted encoding technique to remove Gaussian noise and impulse noise jointly. We encoded the image patches over a set of PCA dictionaries learned offline, and weighted the coding residuals to suppress the heavy tail of the distribution. The weights were adaptively updated to decide whether a pixel is heavily corrupted by impulse noise or not. Meanwhile, image sparsity prior and nonlocal self-similarity prior were integrated into a single nonlocal sparse regularization term to enhance the stability of weighted encoding. The results clearly demonstrated that WESNR outperforms much other state-of-the-art mixed noise removal methods

ADVANTAGES

- Runs much faster than the previous systems.
- More stability was provided for weighted encoding

SYSTEM REQUIREMENT:

HARDWARE REQUIREMENTS:

Processor	:	Intel
Ram	:	2 GB (Minimum)
Monitor	:	15” COLOR
Hard Disk	:	500 GB
Keyboard	:	STANDARD 102 KEYS
Mouse	:	3 BUTTONS

SOFTWARE CONFIGURATION:

Operating System	:	Windows 7 / 10
Environment	:	MATLAB
Matlab	:	Version 18a

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