A Comparative Analysis of Noise Reduction Filters in Images

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Abstract: *Digital images are having a lot of noise. There are a large number of techniques which are used for removing noise from the images. In this paper JSR technique is used for removing mixed noise (GN, IN) from the images. This paper also implements WJSR techniques. WJSR techniques apply on dissimilar pixels and it assign weight to group of pixels. WJSR are also implements on mixed noise removing and it is used for grouping the non local similar image patches. This paper shows the result of JSR and WJSR techniques.*

Key Words: *Digital images, Noise, Joint sparse Representation (JSR), Weighted Joint Sparse Representation (WJSR), Denoising.*

Abbreviations & Acronyms

JSR	**Joint sparse representation**
WJSR	**Weighted joint sparse representation**
IN	**Impulse Noise**
GN	**Gaussian Noise**

1. INTRODUCTION:

Digital image are those images which are always corrupted due to process of transmission and acquisition. Noisy image usually cannot be directly used for future image applications (i.e. enhancement, recognition and super-resolution) due to its low characteristics. Consequently image denoising is the crucial inverse problem that aims to recover the original image as much as possible from the noisy image. Fortunately, encountered the noise can be detected by two types, namely (GN) Gaussian noise and (IN) Impulse noise. Gaussian noise is usually developed into images due to the thermal motion in the cameras. And Impulse noise is introduced by bit errors or faulty memory locations.

2. LITERATURE REVIEW:

This paper we provide an explanation for the image denoising to remove the noise from the images. Liu L. et.al (2016) proposed a WJSR model to remove mixed noise and it is based on JSR model. Firstly he used JSR model to remove the mixed noise but JSR is easily broke able and damaged to outliers. To remove these drawbacks of JSR it is enhanced to WJSR by using patch matching. Then the results of both techniques are compared and results of WJSR are showing superiority over the JSR [1].Zhou Y. et al. have presented a weighted couple sparse representation model to remove impulse noise (IN). The proposed method achieves better performance in reduction of IN when compared with several state-of-the-art denoising algorithms with respect to both the quantitative measurements and the visual effects [2]. Yue H. et al. have proposed two stage strategy using different filtering approaches. In first stage graph based optimization is proposed to improve accuracy in external denoising. Preliminary result can be obtained by combining internal and external denoising patches. In the second stage, they propose reducing noise by filtering of external and internal cubes, respectively, on transform domain. The final denoise image is obtained by fusing the external and internal filtering results. Experimental results show that proposed technique gives best results for subjective and objective image [3]. Zhang P. et al. have proposed a new adaptive weighted mean filter (AWMF) for detecting and removing high level of salt-and-pepper noise. This algorithm was enhancement of adaptive mean filter (AMF). After comparing The AMF And AWMF IT was concluded that detection accuracy of AWMF is more than AMF and it could better perform than many other existing filters [4]. Sijbersal J. et al. Proposed an iterative bilateral filter is for denoising magnitude MR images. This iterative bilateral filter improves the denoising efficiency and preserve the edge feature and fine structure in the image. For the comparative analysis, experiments were conducted on both the synthetic and the real MR images, and for the synthetic images, mean SSIM and PSNR are used for the quantitative analysis. The proposed method is compared with the state-of-the-art methods like UNLM, NLML and LMMSE. The visual and quantitative analysis shows that the performance of proposed methods[5]. Yan M. et al. proposed two methods based on blind in painting and _0 minimization to remove the impulse noise. These methods can simultaneously find the damaged pixels and restore the image. By iteratively restoring the image and updating the set of damaged pixels, these methods have better performance than other methods [6]. Rajwade A. et al. have presented an extremely simple algorithm—the higher order singular value decomposition (HOSVD) of similar image patches in conjunction with hard thresholding and averaging. They have demonstrated its excellent empirical performance in comparison with then state-of-the-art algorithms through a large number of experiments on two full databases[7].Chen T. et al. proposed a novel adaptive operator, which forms estimates based on the differences between the current pixel and the outputs of center-weighted median (CWM) filters with varied center weights. The proposed technique consistently yields satisfactory results in suppressing both of the random-valued and fixed-valued impulse noises while still possessing a simple computational structure [8]. Zhu J. et al. have proposed a new de-noising algorithm based on sparse image representation for removing salt-and-pepper noise. It can detect the salt-and-pepper noise efficiently while preserving the structural information. The simulation results demonstrate that this approach provides good de-noising results and outperforms other filters in terms of noise suppression and detail preservation [9]. Zhang J. et al. established a novel and general framework for high-quality image restoration using group-based sparse representation (GSR) modelling, which sparsely represents natural images in the domain of group, and explicitly and effectively characterizes the intrinsic local sparsity and nonlocal self-similarity of natural images simultaneously in a unified manner. Experimental results on three applications: image in painting, deblurring and CS recovery have shown that the proposed GSR achieves significant performance improvements over many current state-of-the-art schemes and exhibits good stability [10].

3. JOINT SPARSE REPRESENTATION TECHNIQUE:

JSR technique is used for removing mixed noise (GN,IN) from the images.

A. NOISE MODEL

When an image is corrupted by Gaussian Noise, it can be developed as **X = Y + N**, where **Y** is the original image, **X** is its observation, and the independent identically distributed (IID.) is N. noise following the zero mean Gaussian distribution(GD). There are two main types of Impulse Noise, namely SPN and RVIN. Let the pixel values be bounded by $(e\ \min, e\ \max)$, then the IN is described as $x_{i,j} = s_{i,j}$ with probability p $(0 \le p \le 1)$, and $x_{i,j} = y_{i,j}$ with probability $1-p$. For SPN, $s_{i,j} \in \{e\ \min, e\ \max\}$, while for RVIN, $s_{i,j} \in [e\ \min, e\ \max]$. In this paper the mixed noise removal problem and the following noise model is considered:

$$X = Y + N + E \qquad (1).$$

Here **E** is a sparse matrix whose nonzero entries obey the SPN or RVIN distribution.

B. SPARSE REPRESENTATION

For a noisy signal **x** = **y** + **n**, **n** is assumed as the GN, the SR model is formulated as

$$\min ||x - D\alpha||_2^2 \quad s.t. ||\alpha||_0 \le L \qquad (2).$$

where $D \in \mathbb{R}^{n \times k}$ is the dictionary, α is the coefficient, and $\|.\|_0$ denotes the $l0$ pseudo norm counting the nonzero elements. The signal is then projected on the subspace to update the coefficient

$$\alpha = \arg\min_\alpha ||\mathbf{x} - D_{\wedge t}\, \alpha||_2^2 \qquad (3).$$

4. WEIGHTED JOINT SPARSE REPRESENTATION

In this technique, we present a denoising algorithm based on WJSR to remove mixed noise (mixed GN and IN) in images by exploring both the self-similarity and the sparse priors.

$$\min ||w \odot (x - D\alpha)||_2^2, \quad s.t. ||\alpha||_0 \le L \qquad (4).$$

where **w** is a weight vector with the same size of **x**, whose entry $0 \le w_i \le 1$ is the weight describing the outlierness of pixel x_i, and denotes the element-wise product. If x_i is corrupted by outlier, then it is assigned with a smaller or no weight ($w_i \to 0$ or $w_i = 0$); otherwise, it is assigned with a larger weight ($w_i \to 1$ or $w_i = 1$). One can see that, with such weights, the influences of outliers are reduced, while the contributions of clean pixels are highlighted. In order to solve (4), a diagonal matrix $W = \mathrm{diag}(\mathbf{w})$ whose ith diagonal entry is w_i is introduced. Then (4) is rewritten as:

$$\min ||\tilde{x} - \tilde{D}\alpha||_2^2, \quad s.t. ||\alpha||_0 \le L \qquad (5).$$

where $\tilde{x} = W\mathbf{x}$ and $\tilde{D} = WD$. Equation (5) can be viewed as decomposing the new signal $\tilde{x}$ on the new dictionary $\tilde{D}$. the diagonal matrix W can be treated as weights to weight each entry of **x** and each row of the dictionary D.

A. PATCH MACHING

The patches searching process in our case is slightly different from the above one, since the image patches in our problem could be corrupted by outliers (e.g., IN) which seriously distort the similarity structures of patches. Therefore, apply the above searching process directly on the raw images will lead to extremely bad results. To overcome this problem, we choose to conduct the similar patch searching process on the pre filtered images rather than on the raw images directly.

$$Xj = (x^s_{j,(1)}, x^s_{j,(2)}, \ldots\ldots, x^s_{j,(P)}) \qquad (6).$$

Xj patch is arranged in descending order of the distances. Patch x^s_j is said to be similar with **x***j* if it is within the first *P* closest patches to **x***j*. The similarity is measured by the Euclidean distance, e.g. $||x_j - x^s_j||^2_2$ the weights are also extracted from the same positions in the weight map corresponding to the similar patch group, and constructed as the weight matrix *Wj*.

B. WEIGHTED JOINT SR

Since the patches in each *Xj* are very similar to each other, it is reasonable to expect that they lie in a subspace. Therefore, we code each similar patch set by the proposed WJSR model

$$\hat{A}_J = \arg min_A \; ||W_j \odot (X_j - DA_j)||^2_2, \quad s.t. ||A_j||_{row,0} \leq L \qquad (7).$$

When the coefficient matrix $\hat{A}_j$ is obtained, the estimate of **x***j* is given as $\hat{x}_j = D\hat{\alpha}_J$, where $\hat{\alpha}_J$ is the first column of $\hat{A}_J$. After all the patches are estimated, the denoised image is then reconstructed by averaging all the overlapping patches. For simplicity, we denote $\hat{y}$ be the denoised image processed by model (7).

5. METHODOLOGY:

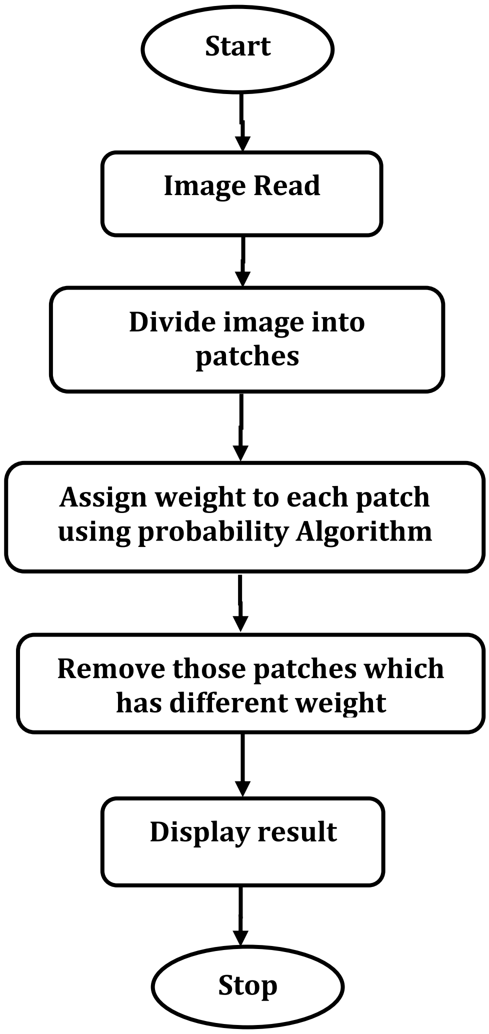


Figure1. METHODOLOGY

6. RESULTS & DISCUSSIONS:

To evaluate and compare the proposed WJSR technique with conventional technique on the basis of following parameters:

A. Mean Square Error (MSE)

The MSE is defined as the cumulative square error between the encoded and the original image:

$$\mathrm{MSE} = \frac{1}{mn}\sum_0^{m-1}\sum_0^{n-1} ||f(i,j) - g(i,j)||^2 \qquad (8)$$

Where, f is the original image and g is the uncompressed image. The dimension of the images is m x n. Thus for efficient compression, MSE should be as low as possible.

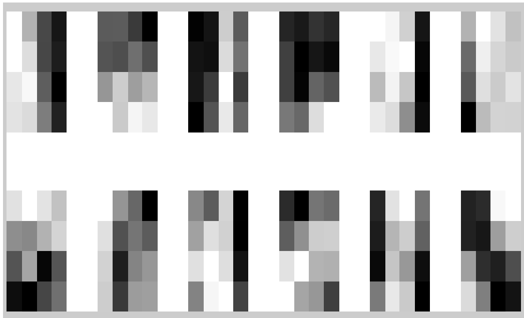
B. Peak signal to Noise ratio (PSNR)

The proportion between maximum possible power of a signal and the power of distorting noise is known as PSNR, which affects the quality of its representation. It is defined by:

$$PSNR = 20log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right) \quad (9)$$

Where is the maximum signal value that exists in our original "known to be good"image. This research work is in MATLAB toolbox. There are following some results which are shown in the form of:

(a) Original Image



(b) Image Patches

(c) Noisy Image

(d) Denoised Image

In (a) original images (b) image patches (c)noisy image (e) denoised image these all images are filtered on various sigmas.

Table 1: Comparison results of JSR & WJSR

σ	PSNR		VIF	
	JSR	WJSR	JSR	WJSR
$\sigma = 5$	30.02	32.10	48.38	50.30
$\sigma = 10$	31.24	31.96	46.03	49.22
$\sigma = 15$	33.78	33.08	40.64	47.49
$\sigma = 20$	32.22	33.94	33.29	36.82
$\sigma = 25$	35.32	36.10	25.14	24.62
$\sigma = 30$	37.42	37.90	27.08	27.99

7. CONCLUSION:

In this research work two techniques are implemented. WJSR technique gives better result for removing mixed noise from images. In future work, WJSR technique will be implemented by using probability based algorithm, The results become better by using (SNR, PSNR, MSE, ACCURACY and EXECUTION TIME) parameters.

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