

Restoration of Images Corrupted by Mixed Gaussian Impulse Noise with Weighted Encoding

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Abstract - Data exchange can be achieved with different types of communication. Data can be text, image, audio and video. During the image transmission the images are affected by many types of noise. Mainly Additive White Gaussian Noise (AWGN), Impulse Noise (IN) and combination of **both called as "mixed noise"**. Removal of mixed noise from the original image is critical and challenging work. The noise spreading is not having any predefined model consisting of heavy tail, due to which quality of image reduces. To remove the mixed noise from the image, many methods exist. These are detection based methods. In this method, locations of the noise are detected and then from these locations noise is removed using some algorithms, based on intensity and amount of noise. But these methods will give poor result, if the mixed noise is strong. Hence this paper implements a new effective method to remove the mixed noise. In this method there is no separate step for detection of different types of noise, instead pixel detection via weighted encoding is done which deals with AWGN and IN simultaneously. This proposed method performs better than existing image denoising methods. It can be applied with multiple types of IN and even in the condition when noise content is more.

Key Words: AWGN, IN, Mixed noise and weighted encoding

1. INTRODUCTION

Image denoising is one of the important and developing areas in the branch of image processing. Noises are unavoidable during image generation, transmission and reception process, due to which quality of image will be reduced. Unwanted information which are added during acquisition or transmission or reception which destroys the quality of the image is called as "noise".

Image restoration techniques aims at recovering the original images. Images are corrupted by degradation such as linear frequency distortion and noise. This paper is based on image corruption due to noise. Image restoration is defined as the method of elimination of degradation in the image using linear or nonlinear filtering. Ultimate goal is to bring the corrupted image into original form or to improve the quality of the denoised image. Denoising process which is also called as "noise removal" is a major difficulty in the branch of image processing. This operation aims at the maximum preservation of fine details, image edges and textures maintaining with respect to noised image in comparison with original image. For this, knowledge of different types of noise distribution is required [4].

There are many types of noise exist, out of which mainly two types of noise are considered in real time application. These are AWGN and IN. AWGN is regularly introduced because of the thermal movement of electrons in camera sensors and in other electronic devices. IN is frequently introduced by malfunctioning of the camera sensor pixels, defective memory segments in hardware and transmission error like bit error. In AWGN, each image pixel which is corrupted will be replaced with a value independently sampled from a Gaussian distribution with zero mean, which is going to add with the gray level of the pixel [5]. The image which is corrupted with IN will be having a portion of its pixels exchanged with values of random noise with the remaining pixels unaltered. There are two types of commonly considered IN, Salt and Pepper Impulse Noise (SPIN) and Random Valued Impulse Noise (RVIN). The image which is degraded by SPIN results in bright pixels in dark regions and dark pixels in bright regions. Image which is degraded by RVIN results in noise in any random pixel locations.

The main aim of this paper is to implement an effective method to remove the mixed noise, using combination of new Weighted Encoding and Sparse Nonlocal Regularization (WESNR) process.

2. LITERATURE SURVEY

This paper consist a new algorithm based on the paper proposed by Dong et al. in the year 2013, in which mixed noise is removed by a unified framework algorithm called as “weighted encoding with sparse nonlocal regularization” [1]. The new method developed will encode the noise corrupted pixel with help of dictionary to remove the AWGN and IN simultaneously. Existing and available mixed noise removal technique, involves two step operations. In first step, impulse noise pixels are detected and then they are removed in second step. This two-step operation is not effective when mixed noise content is more. [2].

Edge preservation is one of the important processes in denoising, which preserves fine details in the image. The information about the edge preservation and the procedure is taken from the work of Liu et al. proposed in the year 2013 [4]. This method is the newest and modified method in the field of edge preservation.

This paper develops the new algorithm based on dictionary method. High quality images are taken offline in advance for the noisy pixel comparison. The high quality images are grouped into some numbers based on *K-means* clustering methods. After *K-means* clustering process, these grouped image pixels are encoded with noisy pixel for the removal of mixed noise by using PCA method [5]. The inputs for this method is taken from the paper of Shao et al. proposed in the year 2014.

In this paper two separate operations are unified into a single frame work called as “sparse nonlocal regularization”. This unified frame work method was proposed by Huang et al. in the year 2014 [6]. In this method, the reference median value was calculated to resolve whether a current pixel is a noise pixel or not. The method based on, if the absolute value among the reference median with a target pixel is higher, then the target pixel is referred as a noise pixel and consequently the mixed noise is removed by switching the operation between the AWGN removal and IN removal. This regularization procedure is combined with sparse nonlocal self-similarity to improve the noise removal capacity in the algorithm.

3. NOISE MODEL

Noise can be categorized by their PDF's and spatial properties like correlation. Filtering a digital image to reduce the noise, while keeping the image fine edge details unaltered, is an essential part and task of image processing. There are many models developed in the process of restoration of the images corrupted by mixed

noise. Different types of filtering technique have been introduced for the removal of mixed noise till date.

Two types of filter commonly used are linear and nonlinear filter. When linear filters are used it yields in image blurring, by which quality of image reduces. As a result, another type of filter called as “nonlinear filters” have been broadly considered due to its improved filtering performance, in terms of mixed noise removal, edge and other details of the image preservation [3].

Nonlinear filter uses median values of the image pixel and its neighborhood pixel, which are strong estimators of noise and protected to high level of mixed noise. But the drawback of this nonlinear filter algorithm is uniform application of the particular filter over the complete image. Due to this, with the noisy pixels noiseless pixels also modified. Fig-1 gives the idea of simple operation flow in denoising. First, input image is considered, for which noises are added. Noise added is a combination of AWGN and IN. Depending upon noise percentage, suitable nonlinear filter is applied to get reconstructed image.

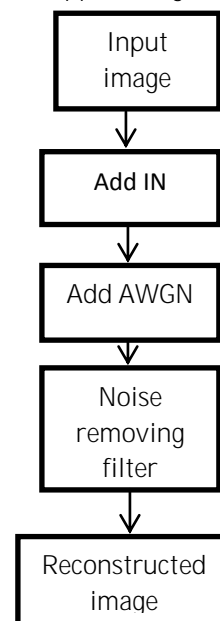


Fig-1: Process flow in the denoising of image

4. WEIGHTED ENCODING MODEL

This paper proposes a new method to remove the mixed noise in which the advanced filter technique is used with respect to other existing filters. The new filters functionality is based on the principle of weighted encoding with sparse nonlocal regularization [2]. Noise removal takes place in many stages, which are explained in following sections.

4.1 Representation of Mixed Noise

Two types of IN that are used in the real time application are SPIN and RVIN. The dynamic range of an image is represented within $[dmin, dmax]$. In the SPIN, the replacement of every image pixel with a given probability takes place having a value $dmin$ or $dmax$. In the RVIN a pixel value is replaced with any random value in the range $[dmin, dmax]$.

In AWGN, weights are chosen according to shape of Gaussian function. This is very much effective for removing the noise and then to make normal distribution. Amount of noise removal by the filter will be same in all directions. Degree of noise removal is governed by variance. This paper considers two types of mixed noise to analyze the image corrupted with noise. First, AWGN mixed with SPIN and second, AWGN mixed with RVIN and SPIN.

Representing an image as X and $x_{i,j}$ be its pixel at location (i, j) . Let Y be the noisy image observed for original image X . For AWGN, the noisy image pixel $y_{i,j}$ in Y can be written as:

$$y_{i,j} = x_{i,j} + v_{i,j} \tag{4.1}$$

In equation (4.1) ' $v_{i,j}$ ' represents the Impulse Invariance Distribution (IID) noise and it follows Gaussian distribution. When IN is considered, dynamic range of Y is $[dmin, dmax]$. The images which are affected by SPIN and RVIN, the noise pixels are within the range of minimum or maximum value and any random values in the dynamic range respectively [1].

The combination of AWGN with SPIN model can be described as:

$$\begin{aligned}
 y_{i,j} &= \text{dynamic range } dmin \text{ with probability } 0.5S \\
 y_{i,j} &= \text{dynamic range } dmax \text{ with probability } 0.5S \\
 y_{i,j} &= x_{i,j} + v_{i,j} \text{ with probability } (1-S)
 \end{aligned} \tag{4.2}$$

The combination of AWGN with SPIN and RVIN model can be described as:

$$\begin{aligned}
 y_{i,j} &= \text{dynamic range } dmin \text{ with probability } 0.5S \\
 y_{i,j} &= \text{dynamic range } dmax \text{ with probability } 0.5S \\
 y_{i,j} &= d_{i,j} \text{ with probability } r(1-S) \\
 y_{i,j} &= x_{i,j} + v_{i,j} \text{ with probability } (1-r)(1-S)
 \end{aligned} \tag{4.3}$$

Here $d_{i,j}$ represents the uniformly distributed noise within the range of $[dmin, dmax]$. Here ' S ', ' r ' represents levels of SPIN and RVIN which are added respectively. This defines the level of the noise content in the image [1].

4.2 Denoising Model

Traditional method of mixed noise removal consists of two step framework. In first step, the IN pixels are detected and then replaced. In second step, some AWGN removal methods are applied to evaluate the AWGN of the image. But this method is not suitable for either AWGN mixed with SPIN or RVIN, if the noise content is more.

In the proposed mixed noise removal method which is shown in Fig-2, does not perform removal of AWGN and detection of impulse pixel separately, it combines the two different tasks in a unified framework. This paper proposes a novel weighted encoding model to remove mixed noise, which is not having the separate impulse pixel detection step and it can process the combination of noise AWGN and IN at the same time. The nonlocal self-similarity and sparsity of the natural images are also integrated into the proposed model to make it powerful for mixed noise removal [1].

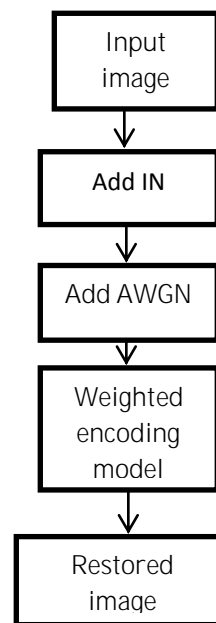


Fig-2: Process flow of the weighted encoding model.

4.3 Denoising Method

Noisy image is represented along with original image as:

$$Y = X + n \tag{4.3}$$

In equation (4.4), X is an original image and n is noise. Vector form of original image can be written as:

$$x_i = R_i X \tag{4.5}$$

In equation (4.5), ' i ' is the i^{th} patch vector of image of size $\sqrt{N} \times \sqrt{N}$, it varies from $(0, 1, 2, \dots, N)$ and ' R_i ' represents the extract patch matrix operator with respect to patch x_i of the image X . Vector representation of the original image can be written as $X \in R^N$. Then equation (4.5) can be

written as $x_i = R_i x \in R^N$. With reference to sparse representation theory, set of normalized basis vector called as "dictionary", represented as ' ϕ ' can be calculated for the image. For i^{th} image patch a dictionary ' ϕ ' is selected. This can be written as:

$$\phi = [\phi_1, \phi_2, \phi_3 \dots \phi_n] \in R^{N \times M} \quad (4.6)$$

Equation (4.6) is a code set of image patches obtained from dictionary. Selection of dictionary is done such that image patch can be approximated as:

$$X = \phi \alpha \quad (4.7)$$

With the equation (4.7), the entire image can be reconstructed by averaging all reconstructed patches with help of dictionary. Here ' α ' is a sparse coding vector with only few nonzero entries. This sparse code vector is determined from sparse coding of the image over the dictionary. To sparsely code x_i the dictionary is considered as $\phi_j \in R^N$ where ' N ' is the j^{th} atom of ' ϕ '.

In image denoising, the observation of image X is noise corrupted, and it is possible to encode the noisy observation Y over ' ϕ ' to obtain the expected value of ' α ' [2].

4.4 Residual Calculation

Distribution of the noise in the image pixel has heavy tails. Main source for this heavy tail is IN, of the mixed noise. By using l_2 normalization technique this heavy tail can be eliminated. Heavy tail generates damages to the original image which is represented in terms loss as given in the equation (4.9). The overall heavy tail of complete image is called as "residue". Residues are classified separately for AWGN and IN. The pixel which is observed with AWGN, follow Gaussian distribution and they assigned with weight which is near to 1 for l_2 normalization calculation. The pixel observed with IN assigned with weight less than 1.

The residue of the image can be written as:

$$e = [e_1, e_2, e_3 \dots e_n] = (Y - \phi \alpha) \quad (4.8)$$

It is assumed that $e_1, e_2, e_3 \dots e_n$ are IID samples. The robust estimation technique to minimize the loss is given as:

$$Loss = \min \sum_{i=1}^N f(e_i) \quad (4.9)$$

Function ' f ' in equation (4.9) controls the contribution of each residual to the overall loss of the image.

4.5 Weighted Encoding

In the weighted encoding model ' W ' is a diagonal weight matrix and its element ' W_{ii} ' is automatically determined and assigned to pixel at location ' i ' which is given in

equation (4.10). This weight ' W ' represents similarity between neighborhoods of the each pair of pixels considered. The image pixels which are corrupted with IN will have smaller weights to minimize their effect on the encoding of Y with respect to the dictionary ' ϕ ', while the weights with uncorrupted pixels will be considered to 1. In this algorithm, the dictionary ' ϕ ' is pre learned from clean natural images. The pixel corrupted by IN having higher coding residuals and it can be used to guide the setting of weight ' W_{ii} ' and is inversely proportional to the strength of coding residual [1]. One simple and appropriate equation of ' W_{ii} ' is given as:

$$W_{ii} = \exp(-a e_i^2) \quad (4.10)$$

Once ' W ' is calculated as per the equation (4.10), process becomes ready to l_2 normalization technique which also includes sparse coding problem. This is solved by considering many iterations of weighted encoding operation. For next operation, let ' V ' is a diagonal matrix which is initialized as identity matrix and then in the $(k + 1)^{th}$ iteration, each and every element of diagonal matrix ' V ' is updated as:

$$V_{ii}^{(k+1)} = \lambda / \sqrt{((\alpha_i^k - \mu_i) + \epsilon^2)} \quad (4.11)$$

where ' ϵ ' is a scalar and ' α_i^k ' is the i^{th} element of coding vector ' α ' in the k^{th} iteration. The parameter ' λ ' is regularization parameter, which plays an important role. If the value of ' λ ' is zero which means that, there is no noise content. As the ' λ ' value increases, shows the noise content in the image. Then ' α ' can be written as:

$$\alpha^{(k+1)} = (\phi^T W \phi + V^{k+1})^{-1} (\phi^T W Y - \phi^T W) + \mu \quad (4.12)$$

After iteratively updating of diagonal matrix ' V ' and ' α ', the actual value of ' α ' will be effectively obtained.

4.6 Dictionary

In this paper it is assumed that the dictionary ' ϕ ' is obtained first and later it is used in the algorithm. The selection of dictionary is an important issue of the sparse coding and reconstruction of an image. In particularly, learning dictionaries from natural image patches is an important process in image restoration. In this paper, a set of local PCA dictionaries are considered, offline from five high quality images with respect to original.

The image patches are divided into many clusters. Each cluster consists of many patches with similar patterns. A complete set of dictionary can be obtained from the each cluster. PCA technique is used to obtain the dictionary. For the image patches to be coded, the dictionary value which

is more relevant is considered with the noise pixel patch to replace.

Total number of 2401 × 200 patches are extracted from the high quality images and then they are divided into 200 clusters with help of *K-means* clustering algorithm. It is simplest method in which clustering is done by iterative procedure. It clusters the data by iteratively computing a mean intensity for each class and segmenting the image by classifying each pixel in the class with closest mean. Clustering is the technique in which relationship among the patterns of the data set by organizing the patterns into group of clusters such that pattern within a cluster are more similar to each other than patterns belonging to different clusters.

5. WEIGHTED ENCODING ALGORITHM

The proposed weighted encoding algorithm results in better performance with respect to mixed noise removal. This method can handle the combination of mixed noise that is, AWGN + SPIN and AWGN + SPIN + RVIN and runs very much faster than any other methods. The superiority in the denoising operation of weighted encoding with respect to other methods is achieved from the unified frame work of weighted encoding operation and sparse nonlocal regularization operation [2].

This paper considers two types of noise. First, the mixture of AWGN + SPIN is considered. For this mixed noise, AMF (Adaptive Median Filter) is used at the initial stage for the removal of SPIN. For the mixed noise AMF is applied over the noisy image Y to obtain an initialized image vector denoted as $x^{(0)}$ and then residue 'e' is initialized as:

$$e^{(0)} = Y - x^{(0)} \tag{5.1}$$

Second, the mixture of AWGN + RVIN + SPIN is considered. For this type of mixed noise AMF cannot be applied directly over the noisy image Y . Hence in this case, the residue 'e' is modified as:

$$e^{(0)} = (Y - \mu_y) * 1 \tag{5.2}$$

In equation (5.2), ' μ_y ' is the median value of all the pixels in the noisy image Y and '1' is a column vector with all elements value as 1. Then weighted encoding and residual calculation is performed, with the initialized coding residual ' $e^{(0)}$ '.

The operation taking place in AMF is spatial processing, which is to preserve the fine details of the original image and smooth edges of the original images which are corrupted with noise, along with the operation of IN removal. A pixel which is different from majority of neighbors, as well as being not structurally aligned with those pixels to which it is similar is considered as IN. These noise pixels are then replaced by median pixel value of the pixels in the neighborhood which are already done

with the noise testing. These processes remove the IN in the initial stages and smooth the other noises. The main procedure of the proposed weighted encoding based mixed noise removal model is summarized in below algorithm.

Input: Generate dictionary ' ϕ ' over the noisy image Y ;

Residue 'e' is initialized by Eq. (5.1), (5.2);

Weight matrix 'W' is initialized by Eq. (4.10);

Initialize the median value to 1.

Output: Reconstructed image X .

Loop: Compute the value of $k = 1, 2 \dots k$;

Calculate $\alpha^{(k+1)}$ with Eq. (4.12);

Calculate $x^{(k)} = \phi \alpha^{(k)}$ with updating the nonlocal coding vector;

Calculate the residue with equation $e^{(k)} = Y - x^{(k)}$;

Compute the weights of matrix 'W' with ' $e^{(k)}$ ', using Eq. (4.10);

End

Denoised image is output, obtained as $x = \phi \alpha^{(k)}$.

The process flow diagram, as shown in Fig-3 gives the brief operation flow of the new method using weighted encoding with sparse nonlocal regularization.

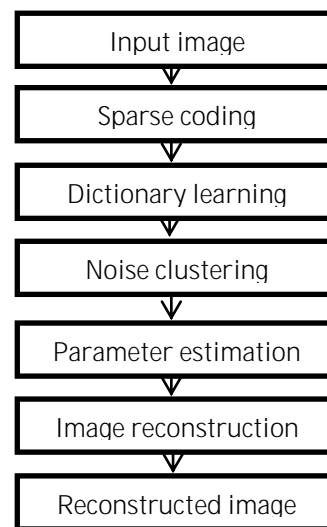


Fig-3: Process flow of new WESNR model

6. RESULT AND PERFORMANCE ANALYSIS

The Experiment is carried out to demonstrate the performance of the weighted encoding algorithm. The parameter setting must be done as a basis for the algorithm. AMF is used first and then weighted encoding with the offline dictionary is considered in the paper.

Experiments can be conducted on any standard images like Lena, F16, Leaves, Boat, Couple, Fingerprint, Hill, Man, Peppers and Painting. In this paper algorithms run under the MATLAB R2010a programming environment with version 7.10.0. MATLAB is installed in a system consisting of Intel Core i5 CPU with 2.53 GHz consisting of 4 GB RAM operating with 64-bit operating system.

This experiment considers two types of mixed noise: AWGN + SPIN, and AWGN + RVIN + SPIN. For AWGN + SPIN mixed noise, the standard deviation of AWGN varies with $\sigma = 10, 20, 25$ and the SPIN ratio varies with $S = 30\%, 40\%, 50\%$ respectively. For AWGN + RVIN + SPIN mixed noise, the standard deviation of AWGN varies with $\sigma = 5, 10, 15$ and the RVIN ratio varies with $r = 5\%, 10\%, 15\%$ and the SPIN ratio varies with $S = 30\%, 40\%, 50\%$ respectively.



Fig-4: Original image of boat

Fig-4 shows the original boat image for introduction of noise. This image is having a size of 512×512 .

Fig-5 shows the AWGN added image. From the image it can be observed that, noise content is uniformly distributed over the entire image. In this algorithm standard deviation considered is $\sigma = 10$ for original image.



Fig-5: Image corrupted by additive white Gaussian noise with $\sigma = 10$

Fig-6 shows the IN introduced image. Here SPIN introduced with noise level $S = 30\%$ and RVIN introduced with noise level $r = 10\%$. These particular values are selected only for proper observation of the noise distribution. Any values can be considered and accordingly noise will be distributed over the entire image. After IN introduction, noise distribution is higher compared with AWGN, which means that IN is stronger noise.

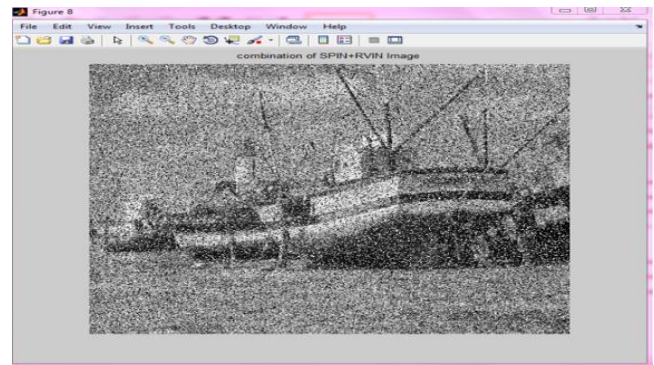


Fig-6: Corrupted image with AWGN + RVIN + SPIN

Fig-7 shows the denoised image of the corrupted image applied with the AMF. This removes the little portion of the noise but not in detail. In order to remove the noise in depth no filter is available than weighted encoding model.



Fig-7: Denoised image with adaptive median filtering

Fig-8 shows the final denoised image after applying weighted encoding model over the adaptive median filtered image. In this image fine details are preserved along with edges. This is possible due to sparse nonlocal regularization process in weighted encoding. Comparatively this denoised image is very much clear and resembles with the original image. This algorithm holds good for any combinations of the noise and noise parameters.



Fig-8: Final denoised image after weighted encoding process

With the result images it is clear that, final weighted encoded image is almost resembles with original image which means that it preserves the fine details. It is important to analyze the performance of weighted encoding model with other type of denoising model to prove the superiority of the newly developed model.

3. CONCLUSIONS

Weighted encoding model for mixed noise removal using sparse nonlocal regularization is implemented successfully. The distribution of mixed noise, which is a combination of AWGN and IN, is having more irregularity than Gaussian noise alone and normally it has a heavy tail in its distribution. To overcome from this difficulty, the weighted encoding technique is adopted to remove AWGN and IN together. This paper encodes the image patches over a set of PCA dictionaries which is obtained offline and weighted the coding residuals to eliminate the heavy tail of the distribution. The weights of the noisy image are adaptively updated for deciding whether a pixel is heavily corrupted by IN or not. In this paper along with weighted encoding, image sparsity and nonlocal self-similarity processes are integrated into a single unified framework, which is called as nonlocal sparse regularization process to improve the stability and efficiency of weighted encoding model over the noisy image.

REFERENCES

- [1] Weisheng Dong, Lei Zhang, Guangming Shi, and Xin Li, "Nonlocally Centralized Sparse Representation for Image Restoration", *IEEE Transactions on Image Processing*, Vol. 22, No. 4, April 2013.
- [2] Weisheng Dong, Lei Zhang, Rastislav Lukac, and Guangming Shi, "Sparse Representation Based Image Interpolation with Nonlocal Autoregressive

Modeling", *IEEE Transactions on Image Processing*, Vol. 22, No. 4, April 2013.

- [3] Yu-Mei Huang, Lionel Moisan, Michael K. Ng, and Tiejiong Zeng, "Multiplicative Noise Removal via a Learned Dictionary", *IEEE Transactions on Image Processing*, Vol. 21, No. 13, November 2012.
- [4] J. Liu, X. C. Tai, H. Y. Huang, and Z. D. Huan, "A Weighted Dictionary Learning Models for Denoising Images Corrupted by Mixed Noise", *IEEE Transactions on Image Processing*, Vol. 22, No. 3, pp. 1108-1120, March 2013.
- [5] Ling Shao, Ruomei Yan, Xuelong Li, and Yan Liu, "From Heuristic Optimization to Dictionary Learning: A Review and Comprehensive Comparison of Image Denoising Algorithms", *IEEE Transactions on Cybernetics*, Vol. 44, No. 7, July 2014.
- [6] De-An Huang, Li-Wei Kang, Yu-Chiang Frank Wang, and Chia-Wen Lin, "Self Learning Based Image Decomposition with Applications to Single Image Denoising", *IEEE Transactions on Multimedia*, Vol. 16, No. 1, January 2014.

BIOGRAPHIES



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