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***Research paper***

# Convolutional Neural Network Based Image Denoising for Better Quality of Images

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**Abstract**

This work gives a survey by comparing the different methods of image denoising with the help of wavelet transforms and Convolutional Neural Network. To get the better method for Image denoising, there is distinctive merging which have been used. The vital role of communication is transmitting visual information in the appearance of digital images, but on the receiver side we will get the image with corruption. Therefore, in practical analysis and facts, the powerful image denoising approach is still a legitimate undertaking. The algorithms which are very beneficial for processing the signal like compression of image and denoising the image is Wavelet transforms. To get a better quality image as output, denoising methods includes the maneuver of data of that image. The primary aim is wavelet coefficient modification inside the new basis, by that the noise within the image data can be eliminated. In this paper, we suggested different methods of image denoising from the corrupted images with the help of different noises like Gaussian and speckle noises. This paper implemented by using adaptive wavelet threshold( Sure Shrink, Block Shrink, Neigh Shrink and Bivariate Shrink) and Convolutional Neural Network(CNN) Model, the experimental consequences the comparative accuracy of our proposed work.

***Keywords:*** *Wavelet thresholding, sure shrink, block shrink, neigh shrink, bivariate shrink, CNN model.*

## 1. Introduction

In acquisition and transmission method, the image is get stricken by the noise. Therefore we're the use of exceptional image denoising techniques to cast off the noise from the picture. The principle goal of image denoising is getting a higher best of an original image from the corrupted image. While protecting the characteristics of a signal, Wavelet denoising methods removes the signal noise, without considering the frequency content. Noise effected natural images, denoising becomes powerful by the wavelet techniques because with small number of energy transform values only it has the capacity of reproduce the signal energy. Wavelet thresholding approach is used to take advantage of the wavelet transform capabilities for denoising the image. It expels noise by killing coefficients that are unimportant in respect to some threshold, and ends up being simple and successful, relies upon the decision of thresholding parameter and the decision of this edge decides, as it were, the adequacy of denoising. Denoising algorithm by using wavelet transform contains three steps.

- Applying wavelet transform to the image corrupted by noise.
- In keeping with a few rule, wavelet coefficients with noise are modified.
- Applying inverse wavelet transform for the modified coefficients.

The picture denoising problem may be formulated as given,

Let B (i, j) denotes noisy image, A (i, j) represents image without noise and Z (i, j) be the noise

$$B(i,j) = A(i,j) + SZ(i.j) \quad (1)$$

The focus is desired signal estimation with the accuracy in response to a given criteria.
The computed problem in the wavelet domain is given as,

$$Y(i.j) = W(i,j)Z(i,j) \quad (2)$$

Where Y(i,j) indicates the wavelet coefficient with noise, W(i,j) represents real coefficient and Z(i,j) indicates the noise occurred.
An experimental result calculates two parameters such as Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE). By computing these two parameters, the overall performance of the image denoising algorithm is analyzed.

## 2. Wavelet Thresholding

Let A={Aij, i, j=1,2,…M} represents the original image which has to be recovered of M*M matrix, where M indicates some value i.e, integer power of 2. The image is affected by white gaussian noise Zij during the transmission and the standard deviation is nij ~ N (0, _2) and at the end of the receiver, the noisy observations Bij= Aij+ Zij is obtained. The primary purpose isA signal estimation from the Bij noisy observations such that MSE is lower. Let W represents the 2-D orthogonal DWT (Discrete Wavelet Transform) and

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$W^{-1}$ represents the inverse of that. Then Y=WB denotes the matrix with wavelet coefficients of B. B consist of four sub bands i.e, LL, LH, HL and HH. The HHk, HLk, LHk are called as detailed coefficients, where k gives the scale altering from 1,2,…J and here J is the total decompositions number. At scale k, N/2k*N/2k is the sub band size. The LLJ sub band is the minimum resolution residue. To obtain X, the wavelet thresholding method processes every Y coefficients through detailed sub bands with a soft threshold function. The estimation of denoised signal is inversely transformed to $A=W^{-1}$ X. For experiments, we are using soft thresholding instead of hard thresholding function because when compared to hard thresholding, soft thresholding gives most visual quality images. Later the reason is discontinuous and especially when the noise is notable, recovered images get corrupted with the artifacts.

### 2.1. Sure Shrink

One of the thresholding is a Sure Shrink. In this the threshold which is applied is sub-band adaptive threshold. An individual threshold is calculated for each and every particular sub-band depends upon SURE (Stein's unbiased estimator for risk), the minimization of mean squared error is the primary focus of the Sure Shrink. Given equation defines the Mean Squared Error,

$$MSE = \frac{1}{n^2} \sum_{X,Y-1}^{n} \left(Z(X,Y) - S(X,Y)\right)^2 \quad (3)$$

Where the signal estimate is Z(X, Y),original signal with zero noise is S(X, Y) and n indicates the signal size. In Sure Shrink, the noise is suppressed by thresholding the coefficients of empirical wavelet. The Sure Shrink threshold is denoted by t*. And it is formulated as below,

$$t^* = \min\left(t, \sigma\sqrt{2logn}\right) \quad (4)$$

Where t is a value, Stein's Unbiased Risk Estimator is minimized by that t value.$\sigma$indicates the variance of noise. And an estimate of noise level$\sigma$ was described depends upon the median absolute deviation. Given equation shows the median absolute deviation.

$$\hat{\sigma} = \frac{median\left(\{|g_{j-1,k}|: k = 0,1 \ldots\ldots\ldots 2^{j-1} - 1\}\right)}{0.6745} \quad (5)$$

And n denotes image size. It is smoothness adaptive. Smoothness adaptive means, the reconstructed image contains the changes if the image contains sudden changes or boundaries.

### 2.2. Bivariate Shrinkage

Based on wavelet transform, Bivariate Shrinkage provides better results. Because this function Bivariate Shrinkage depends upon both, parent and its coefficient. Let w1 be the coefficient and w2 is the parent of that coefficient. (The position of w2 is same as the coefficient w1, but at the next coarser scale.) Then

$$y1 = w1 + n1$$

$$y2 = w2 + n2 \quad (6)$$

Where y1 and y2 denotes the w1 and w2 noisy observations, respectively. And n1 and n2 represents samples of noise. Then we can model

$$Y = W + \mathrm{n}$$

$$wherey = (y1, y2)$$

$$w = (w1, w2)$$

$$n = (n1, n2) \quad (7)$$

Given equation defines the Standard MAP estimator for w given corrupted y,

$$\hat{w}(y) = \arg_w^{max} P_{\frac{w}{y}}\left(\frac{W}{y}\right) \quad (8)$$

The above equation can also be expressed as

$$\hat{w}(y) = \arg_w^{max} P_{\frac{w}{y}}\left(\frac{W}{y}\right) P_w^{(W)} \quad (9)$$

$$p_n I(n) = \frac{1}{n^2} * \exp(-n1^2 + n2^2 + 2\sigma n^2) \quad (10)$$

According to the bays rule allows coefficient estimation can be established by using the noise probability densities as well as wavelet coefficient prior density. Here we conclude noise as gaussian, and then the noise is formulated as

$$p_w(W) = \frac{3}{2\pi\sigma^2} * \exp\left(-\sqrt{3}\sqrt{W12} + W2^2\right) /\sigma \quad (11)$$

Coefficients joint in Wavelet transform

$$\hat{w}(y) = \arg_w^{max}\left[\log\left(pn(y - W)\right) + \log\left(pw(W)\right)\right] \quad (12)$$

By using equation (7)

$$\hat{w}(y) = \arg\max_w\left[\log\left(P_n(y - W)\right) + \log\left(P_W(W)\right)\right] \quad (13)$$

Let us describe

$$f(w) = \log(P_w(W))$$

Afterwards, by using the equations 5.16 and 5.17

$$\hat{w}(y) = \arg max_w[-\frac{(y_1 - w_1)^2}{2\sigma_n^2} - \frac{(y_2 - w_2)^2}{2\sigma_n^2} + f(w) \quad (14)$$

Above equation is identical to compute the given equations

$$y_1 - \frac{\widehat{w_1}}{\sigma_n^2} + f_1(\hat{w}) = 0 \quad (15)$$

$$y_2 - \frac{\widehat{w_2}}{\sigma_n^2} + f_2(\hat{w}) = 0 \quad (16)$$

Where f1 and f2 defines f(w) derivatives in accordance to w1 and w2 respectively.
We know that, f(w) can also be formulated as

$$f(w) = \log(P_w(W))$$

$$\begin{aligned} f(w) &= \log\left(P_w(w)\right) \\ &= \log\left(\frac{3}{2\pi\sigma^2} * \frac{\exp\left(-\sqrt{3}\sqrt{W1^2 + W2^2}\right)}{\sigma}\right) \\ &= \log\left(\frac{3}{2\pi\sigma^2} - \frac{-\sqrt{3}\sqrt{W1^2 + W2^2}}{\sigma}\right) \end{aligned} \quad (17)$$

$$\begin{aligned} f_1(w) &= -\sqrt{3}\frac{w_1}{\sqrt[\sigma]{w_1^2}} + w_2^2 \\ f_2(w) &= -\sqrt{3}\frac{w_2}{\sqrt[\sigma]{w_1^2}} + w_2^2 \end{aligned} \quad (18)$$

By using the above equations (15), (16), (17), and (18) , MAP estimator is given as

$$Z_{\widehat{W}_1} = \frac{\left(\sqrt{y_1^2+y_2^2} - \sqrt{3}\frac{\sigma_n^2}{\sigma}\right) + y_1}{\sqrt{y_1^2+y_2^2}} \tag{19}$$

### 2.3. NeighShrink

In the Neigh Shrink thresholding, relating to the 3the magnitude of the squared sum of all the wavelet coefficients, it means, the local energy, Neigh Shrink thresholds the coefficients of wavelet. And the neighborhood window has may be any size. It may be 3*3, 5*5, 7*7, 9*9 etc. A wavelet coefficient is centered with 3*3 neighboring window and to be shrinked is shown in fig 1.

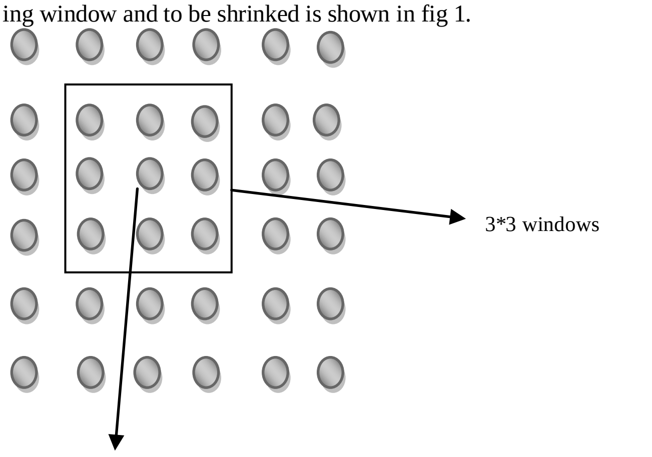


**Fig. 1:** A sketch of the neighboring window with size 3*3 centered at shrinked wavelet coefficient.

$$\Gamma_{i,j} = \left[1 - \frac{T_U^2}{S_{ij}^2}\right]+ \tag{20}$$

Here TU represents universal threshold and Sij2 represents the squared sum of all the coefficients of Wavelet transform in the below window.

$$S_{ij}^2 = \sum_{n=j-1}^{j+1} \sum_{m=i-1}^{i+1} Y_{m,n}^2 \tag{21}$$

Here "+"sign is the very powerful determinant. It keeps the positive value at the end of the formula, it means when it is negative, modifying it into zero. Then, from its noisy counterpart Yij, the coefficient of calculated center wavelet is determined and it is given as,

$$\hat{F}_{ij} = \Gamma_{ij}.Y_{ij} \tag{23}$$

### 2.4. Block Shrink

A kind of approach is Block Shrink, in which a block thresholding with data-driven is done. Block Shrink uses the neighbor wavelet coefficients pertinence by using the block thresholding. The optimal size of block can be resolved as well as the every wavelet sub band's threshold can be determined with the reduction of Stein's Unbiased Risk Estimate (SURE).At the same time the block thresholding keeps or kills all of the coefficients in bunches as opposed to independently. The estimation precision increases in block thresholding with the use of neighbor wavelet coefficient information. The size of block and level of threshold plays a vital role in the performance of block thresholding estimator. The above local block thresholding techniques have a fixed value of block size and threshold. And the regardless of wavelet coefficient distribution, for all the resolution levels identical thresholding rule is applied.

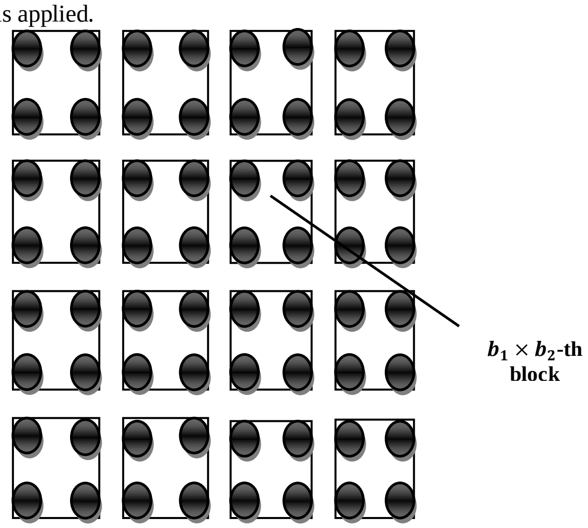


**Fig. 2:** 2*2 Block partition for a Wavelet sub band

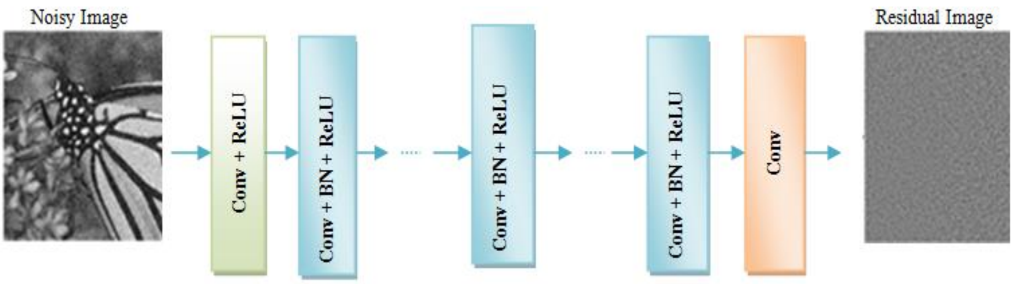


**Fig. 3:** The Architecture of the CNN Network

When we apply wavelet decomposition on an image, multiple sub bands are produced, which is given in the figure2. It is need to segment the every sub band into multiple numbers of blocks.
And with the reduction of Stein's Unbiased Risk Estimate, for all sub bands, the optimal size of block and threshold can be selected by Block Shrink.
For all standard noisy and denoised images, two parameters are calculated. Those are PSNR ( Peak Signal to Noise Ratio) and MSE(Mean Square Error). PSNR is defined as the ratio among signals maximum possible power and the corrupting noise power. By this, the representation fidelity is affected. The scale of PSNR is logarithmic decibel. PSNR can be expressed as below,

$$PSNR = 10log(255/MSE)^2 \tag{24}$$

After denoising the image, PSNR is estimated for denoised image also.
The difference between the estimator and what is estimated is measured by The mean squared error (MSE) or mean squared deviation (MSD) of an estimator. The MSE calculation can be modeled as given below equation.

$$MSE = 1/N \sum_{j=0}^{N-1} (X_j - \bar{X}_j)^2 \tag{25}$$

### 2.5. Denoising Using CNN Model

Here, we are proposing denoising CNN model, i.e, DnCNN, and for multiple general image denoising tasks, DnCNN is extended. Normally, for a specified task, training of DnCNN follows mainly two steps: 1) Design of Network Architecture. and 2) Model Learning from Training Data.

In Design of Network Architecture, to make it suitable for denoising the image, VGG network is modified. Based totally on the effective patch sizes, set the network depth. That patch sizes are used in most recent denoising methods.

In Model Learning from Training Data, residual learning formulation is adopted, and batch normalization is incorporated for speed training with increased performance of image denoising.

## 3. Results

Distinct image denoising techniques are analyzed comparatively with the help of Wavelet transforms in this paper. Special kind of image formats like JPG, TIF, PNG and BMP are considered in this proposed work. Experimental results are got by using four methods of thresholding. i.e, Sure Shrink, Neigh Shrink, Bivariate Shrink and Block Shrink. Using the different images with the noise and on the 512*512 standard test image Lena (Figure 4), different thresholding methods are reported. In experimental results, we are using different kinds of noises like Gaussian noise, Salt and Pepper noise and Speckle noise with the standard deviation of 10. Finally PSNR and MSE values are calculated.[20 and 21]

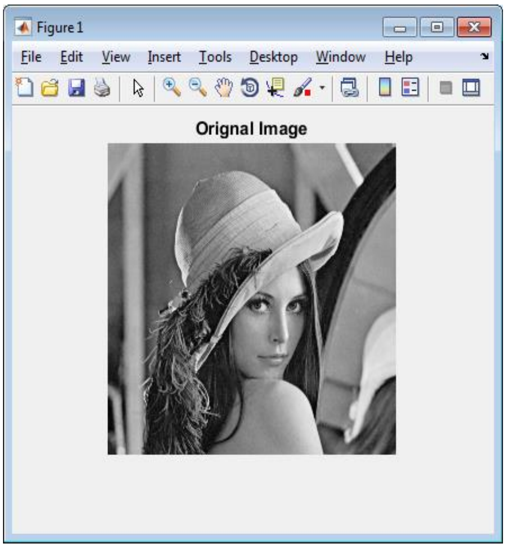


**Fig. 4:** Original image

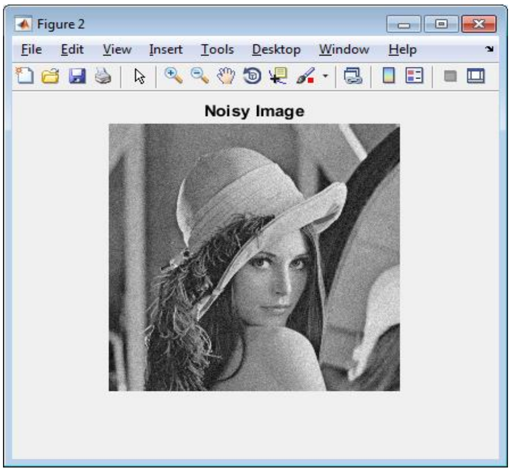


**Fig. 5:** Noisy image

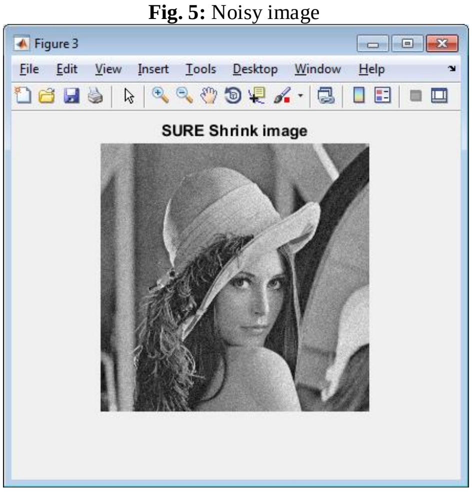


**Fig. 6:** SURE Shrink image

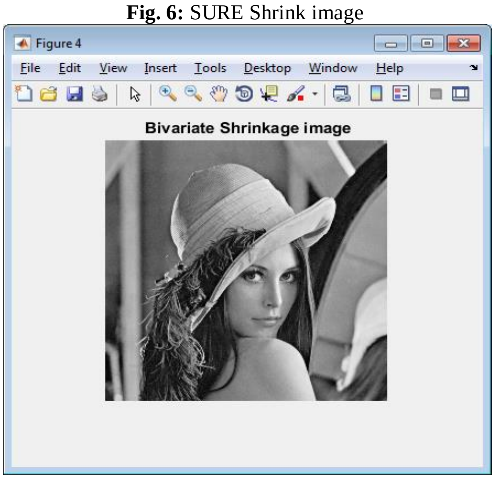


**Fig. 7:** Bivarate shrinkage image

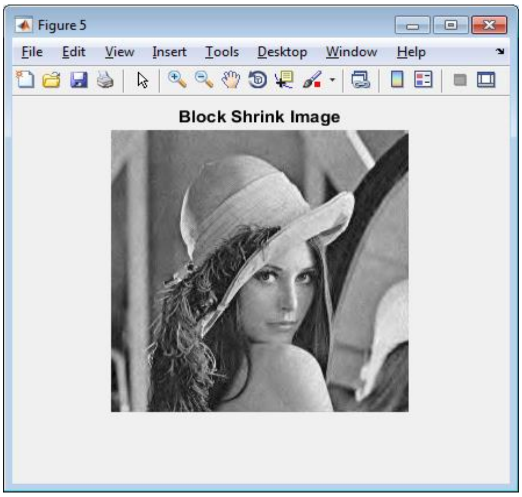


**Fig. 8:** Block shrink image

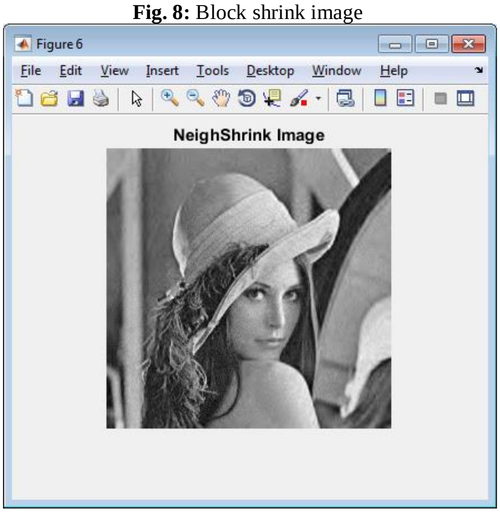


**Fig. 9:** Neigh shrink image

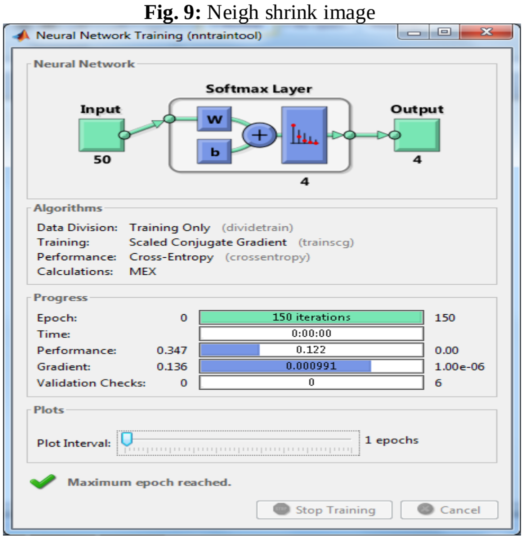


**Fig. 10:** CNN training

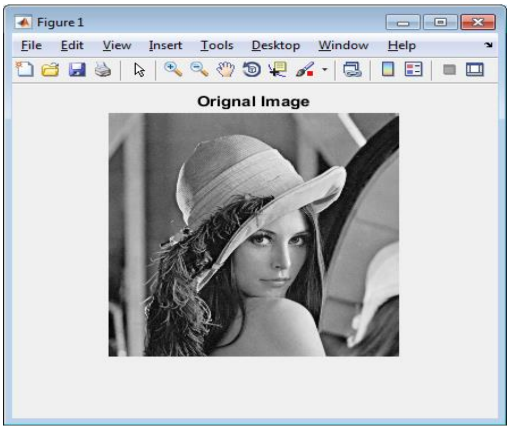


**Fig. 11:** Reconstructed image by CNN model

## 4. Conclusion

This paper gives a comparative evaluation of numerous image denoising strategies using wavelet transforms. Four kinds of thresholding methods (Sure shrink, Bivariate shrink, Neigh shrink, Block Shrink) with various noisy images have experimented and reported the results for the 512×512 standard test images Lena (Fig. 3). They are added with Gaussian noise, salt and paper noise and speckle noise with standard deviations 10. Our results are measured with the aid of the PSNR and MSE. By calculating PSNR value as high and MSE as low.By using CNN we can get Reconstructed Original Image.

## References

[1] Anand BG & Kiran KG "Image Denoising Using Contourlet Transform with Total Variation and Nonlocal Similarity Model", *International Journal of Pure and Applied Mathematics*, Vol.118, (2018), pp.1429-1441.

[2] Zhing G & Xiaohai Y, "Theory and application of MATLAB Wavelet analysis tools", *National defense industry publisher, Beijing*, (2004), pp.108-116.

[3] Gyaourova A, Kamath C & Fodor IK, *Undecimated wavelet transforms for image de-noising* (No. UCRL-ID-150931). Lawrence Livermore National Lab., CA (US), (2002).

[4] Burrus CS, Gopinath RA, Guo H, Odegard JE & Selesnick IW, *Introduction to wavelets and wavelet transforms: a primer*, New Jersey: Prentice hall, (1998).

[5] Abramovich F & Benjamini Y, "Adaptive thresholding of wavelet coefficients", *Computational Statistics & Data Analysis*, Vol.22, No.4, (1996), pp.351-361.

[6] Abramovich F, Sapatinas T & Silverman BW, "Wavelet thresholding via a Bayesian approach", *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, Vol.60, No.4, (1998), pp.725-749.

[7] Cai Z, Cheng TH, Lu C & Subramanian KR, "Efficient wavelet-based image denoising algorithm", *Electronics Letters*, Vol.37, No.11, (2001), pp.683-685.

[8] Donoho DL & Johnstone IM, "Denoising by soft thresholding", *IEEE Trans. on Inform. Theory*, Vol.41, (1995), pp. 613-627.

[9] Zhang XP & Desai MD, "Adaptive denoising based on SURE risk", *IEEE signal processing letters*, Vol.5, No.10, (1998), pp.265-267.

[10] Chang SG, Yu B & Vetterli M, "Adaptive wavelet thresholding for image denoising and compression", *IEEE transactions on image processing*, Vol.9, No.9, (2000), pp.1532-1546.

[11] Chen GY, Bui TD & Krzyzak A, "Image denoising using neighbouring wavelet coefficients", *Integrated Computer-Aided Engineering*, Vol.12, No.1, (2005), pp.99-107.

[12] Donoho DL & Johnstone IM, "Adapting to unknown smoothness via wavelet shrinkage", *Journal of the american statistical association*, Vol.90, No.432, pp.1200-1224.

[13] Stein CM, "Estimation of the mean of a multivariate normal distribution", *The annals of Statistics*, (1981), pp.1135-1151.

[14] Cai TT, "Adaptive wavelet estimation: a block thresholding and oracle inequality approach", *Annals of statistics*, (1999), pp.898-924.

[15] Chen GY, Bui TD & Krzyżak A, "Image denoising with neighbour dependency and customized wavelet and threshold", *Pattern recognition*, Vol.38, No.1, (2005), pp.115-124.
[16] Cai TT & Zhou HH, "A data-driven block thresholding approach to wavelet estimation", *The Annals of Statistics*, Vol.37, No.2, (2009), pp.569-595.
[17] Wink AM & Roerdink JB, "Denoising functional MR images: a comparison of wavelet denoising and Gaussian smoothing", *IEEE transactions on medical imaging*, Vol.23, No.3, (2004), pp.374-387.
[18] Yoon BJ & Vaidyanathan PP, "Wavelet-based denoising by customized thresholding", *IEEE International Conference on Acoustics, Speech, and Signal Processing,* (2004), pp.2-925.
[19] Pizurica A, Wink AM, Vansteenkiste E, Philips W & Roerdink BJ, "A review of wavelet denoising in MRI and ultrasound brain imaging", *Current medical imaging reviews*, Vol.2, No.2, (2006), pp.247-260.3
[20] Akhpanov, S. Sabitov, R. Shaykhadenov (2018). Criminal pre-trial proceedings in the Republic of Kazakhstan: Trend of the institutional transformations. Opción, Año 33. 107-125.
[21] D, Ibrayeva, Z Salkhanova, B Joldasbekova, Zh Bayanbayeva (2018). The specifics of the art autobiography genre. Opción, Año 33. 126-151.