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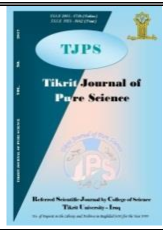

Image De-Noising Based On Wavelet Transform and Block Matching

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Abstract

This paper suggested a de-noising algorithm used in grayscale images. As long as the noisy image does not give the desired view of its features, de-noising is required. The algorithm is based on block matching and wavelet transformation. Euclidean distance for blocks similarity is exploited, which demonstrate more accurate in finding similar blocks depending on soft thresholding. Regarding wavelet transform, a combine of hard thresholding is performed for HH and LH sub-bands while soft thresholding is used in LL and HL sub-bands of the decomposed images. Three types of noise is encountered: Gaussian noise, salt & pepper noise and speckle noise. The measurements are employed to evaluate our work is MSE and PSNR and SSIM. Finally a comparison of the results shows that our method outperforms traditional wavelet using hard or soft thresholding.

1. Introduction

Image degradation is a common issue due to different reasons such as noise of various types (i.e. Gaussian noise, salt & pepper noise and speckle noise). Noise can be defined as unwanted data in image or variation in image brightness or colour. Usually, a de-noising process is the best solution for images afflicted with any type of noise where de-noising goal is to restore images original state by eliminating the noise within it as much as possible, hence contribute in a better view. Normally, the sensor and circuitry of a scanner or digital camera is popular cause of noise generating [1]. At the present time, many algorithms exist and developed for this disturbing problem such as anisotropic diffusion, non-local means, non-linear filters and various transformations [2,3,4].

There is a large literature on wavelet transforms and block matching separates. In contrast, the literature on de-noising using both approaches is very limited. Related works presented as follows:

Yifeng Cheng and Zengli Liu; in 2016 put forward a method that is based on morphological component analysis (MCA) to decomposes an image into texture and structure, for structure part block matching and 3D filtering is used and for texture part all phases biorthogonal transform (APBT) is used and then combine the two parts to get de-noised image [5]. Shunyong Zhou, Xingzhong Xiong and Wenling Xie; In their paper compute the matching blocks, the high and low frequency sub-bands de-noised by the most effective soft threshold, hard threshold that result from the unvarying calculation of noise variance severally. Finally, LL sub-band is sharpened [6]. Sara Parrilli, Mariana Poderico, Cesario Vincenzo Angelino, and Luisa Verdoliva; Presented the scheme of the block-matching 3-D algorithm, recently proposed for additive white Gaussian noise de-noising, then A similarity calculation is used for the block-matching, the wavelet shrinkage is evolved using an additive noise model and find the better local linear minimum-mean-square-error estimator in the wavelet domain [7]. B. Jai Shankar and K. Duraiswamy; Proposes both hard and soft are used in wavelet transform. But around discontinuities it creates a Gibbs phenomenon. The Gibbs oscillations are reduced using transformation domain and block matching is used for improvement of SNR. [8].

Transforms encountered for various signal processing applications like filtering, pattern recognition, restoration, spectrum estimation, signal enhancement, localization and compression [9]. The wavelet transform is one of famous algorithms. The basic idea of the wavelet transform is that the transformation must affect time extension without the shape. Of course, this can be done by choosing the proper function. Thresholding plays an important role in wavelet transform where the image basically divided into four basic sub-bands depend on the decomposition level. Another approach subjected in this paper is block matching. The concept of block matching is to divide the noisy image into blocks, these blocks are matched among them to find the similarity of them and then grouped to together. Block matching depends on a fixed threshold in the process.

2. Block Matching

Block matching is a powerful tool to present the similarity in noisy images. The similar image blocks for a searched neighborhood is computed by adjoining the similarity to a reference one. Similarity in image may pass a certain threshold value to gain a similar block to form a group of similar one pixel. The block similarity is calculated by the following definition [10]:

$$D\left(K_{G_R}, K_G\right) = \frac{\left\|\gamma'\left(N_{2D}^{ht}\left(K_{G_R}\right)\right) - \gamma'\left(N_{2D}^{ht}(K_G)\right)\right\|_2^2}{\left(B_1^{ht}\right)^2} \quad \ldots. (1)$$

where $\gamma'$is the hard thresholding and N_{2D}^{ht} denote the normalized 2-D linear transform of the block K_{G_R} and K_G, $\|\bullet\|_2$ refer to the L^2–norm. From equation (1) a set of blocks $S_{G_R}^{ht}$ can be gained of the coordinates of the blocks that are similar to K_{G_R}[10] :

$$S_{G_R}^{ht} = \left\{k \in K \mid D\left(K_{G_R}, K_G\right) < N_{match}\right\}, \ldots. (2)$$

where N_{match} Is the farthest distance between the two blocks to be take into account similar. Figure (1) below shows the order of the blocks that similar to the reference block.

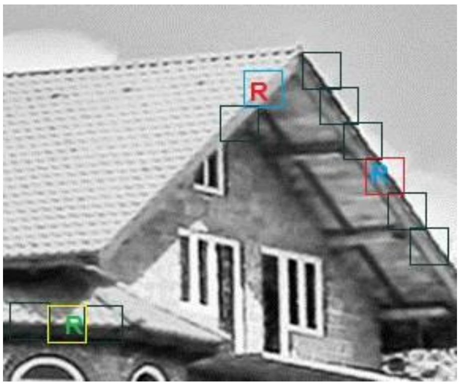


Figure (1): Matching block with its reference block marked with "R".

3. Wavelet Transform

The aim of wavelet de-noising algorithm is to quell the noise occurrence of a signal n (x) by dismissing the noise g (x) to recover the encrypted signal s (x), the model is following the form:

$$n(x) = s(x) + g(x) \quad ...(3)$$

At high frequencies, wavelet provide indigent frequency resolution, while at low frequencies, it shows a good frequency resolution. Analyzing wavelet (mother wavelet) $\psi(x)$ of orthogonal basis is formatted as:

$$\psi_{(a,Y)}(x) = 2 - \frac{a}{2}\, \psi(2^{-a} - Y) \ldots (4)$$

Where a gives the wavelet width and y gives its position in index a are integers that scale the analyzing function ψ to produce wavelets. However, the mother function rescaled by the following equation:

$$R(x) = \sum_{J=-1}^{M-2} (-1)^{j}_{W_{j+1}} + \psi(2x + j) \ldots (5)$$

where $R(x)$ is the scaling function for mother function ψ and W_j are the wavelet coefficients. Choosing the coefficients is one of the advantageous of wavelet to be an appropriate to be de-noised. Daubechies developed a particular or set of wavelet systems which contribute polynomial attitude [11]. In wavelet, it is important to select the right filter for the decomposed image [12]. The image basically is divided (decomposed) into four sub-images, each one of size $I/2 \times I/2$ contain information of the different frequencies. The LL sub-band is the approximation coefficient, which is filtered by low-pass filter for both row and column. The HH sub-band is the result of high-pass filter for both row and column and contain high frequencies. The HL represents the horizontal information while the LH represent the vertical information and both are the result of low-pass filter for rows and high-pass filter for columns, figure (2) below shows those four sub-bands.

LL	HL
LH	HH

Figure (2): Scheme of level 0 decomposition [12]

3.1 Types of Thresholding

Thresholding is very important step in wavelet de-noising; it relies on threshold selection and type of method. It is commonly used in noise reduction, image comparison and recognition [13]. Threshloding is non-linear operation for the coefficients of noisy signal. It can be performed by comparing the value of the corrupted coefficients with the value so called threshold value. Two types of thresholding will be discussed in the next two sub-sections, hard thresholding and soft thresholding.

3.1.1 Hard Thresholding

Also called kill/keep, if the value of the coefficient is below the threshold value it is set to zero. It can be formulated as [14]:

$$C(x) = \begin{cases} x, ni|x| > t \\ 0. ni|x| \le t \end{cases} \ldots (6)$$

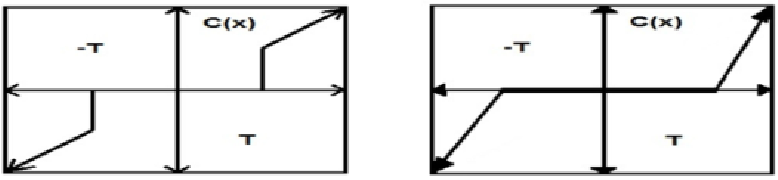
The graphical representation of hard threshold is in figure (3 -A).

3.1.2 Soft Thresholding

It is the dilation of hard thresholding, but shrinking the nonzero coefficients towards zero. It can be formulated as [15]:

$$C(x) = \begin{cases} x - t, ni\ x \ge t \\ x + t, ni\ \le -t \\ 0, ni\ |x| < t \end{cases} \ldots (7)$$

The graphical representation of soft threshold is in figure (3 - B).



(A) (B)

Figure (3): (A) Hard thresholding (B) Soft thresholding[13]

4. Proposed Algorithm

The proposed system is concerned to eliminate the noise form the image. Most of the information in the image bound in big valued coefficient when wavelet is apply to the image. Wavelet transform (WT) is incorporated due its coefficients that provide, and its advantage in many image de-nosing application [16] [17]. In addition, the researchers suggests to use a combine hard thresholding and soft thresholding from the equation (6) and equation (7), where hard thresholding is used for LH and HH sub-bands and soft thresholding is applied to HL LL sub-bands as shown in figure (4):

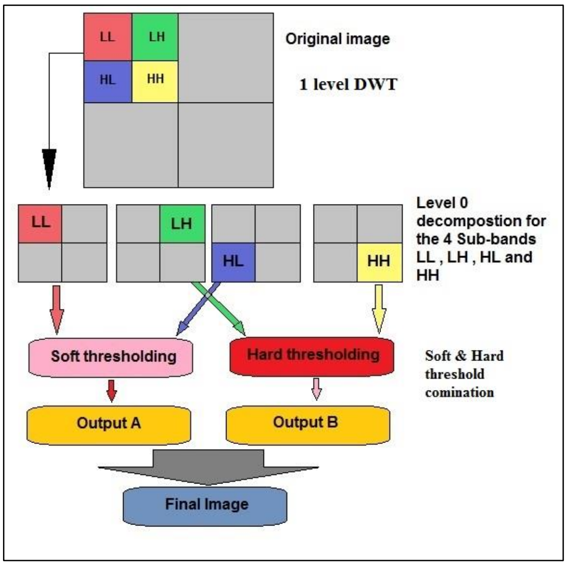


Figure (4): Scheme of hard and soft threshold combination

Furthermore, the researchers proposes Euclidian distance to be used to in calculating similarity distance between similar blocks which demonstrates a more accurate in calculating the similarity distance [18], equation (2) to be re-define as:

$$S_{G_R}^{st} = \left\{k \in K \mid D(K_{G_R}, K_G) < \left\| n(K_{G_1}) - n(K_{G_2}) \right\|_2^2, a\right\}, \quad .... (8)$$

where a is the standard division of Gaussian kernel and $\left\| n(K_{G_1}) - n(K_{G_2}) \right\|_2^2$ is the Euclidian distance. In addition, the researchers replaces the step of hard thresholding γ' with soft thresholding γ'' in equation (1) to be formulated as:

$$D(K_{G_R}, K_G) = \frac{\left\|\gamma''\left(N_{2D}^{st}(K_{G_R})\right) - \gamma''\left(N_{2D}^{st}(K_G)\right)\right\|_2^2}{\left(B_1^{ht}\right)^2} \quad .... (9)$$

The reason to do that because as mentioned before, the researchers suggests to use both hard and soft thresholding in wavelet transform, hence, practically, repeating hard thresholding for the same image in different stages of the algorithm causes image blur and more inaccurate details while soft thresholding with low threshold value will not give that effect, as well as soft thresholding have superior over hard thresholding in low level decomposition [19]. Figure (5) shows the proposed algorithm. The following steps will summarize the proposed algorithm:

Step 1: Load noisy image.

Step 2: Dividing the image into blocks using the block matching technique of the equation (9) and find the similar blocks using equation (8).

Step 3: Apply proposed wavelet transform to each group of blocks obtained in step (2).

Step 4: Apply a combine soft thresholding for LL and HL sub-bands and hard thresholding for HH and LH sub-bands.

Step 5: Run Inverse wavelet transform (IWF)

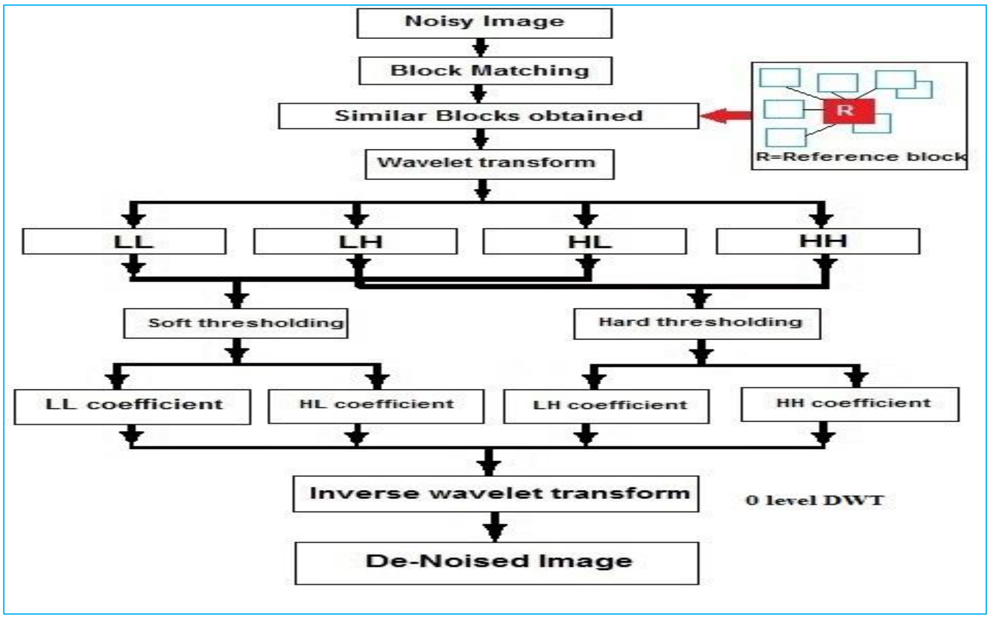
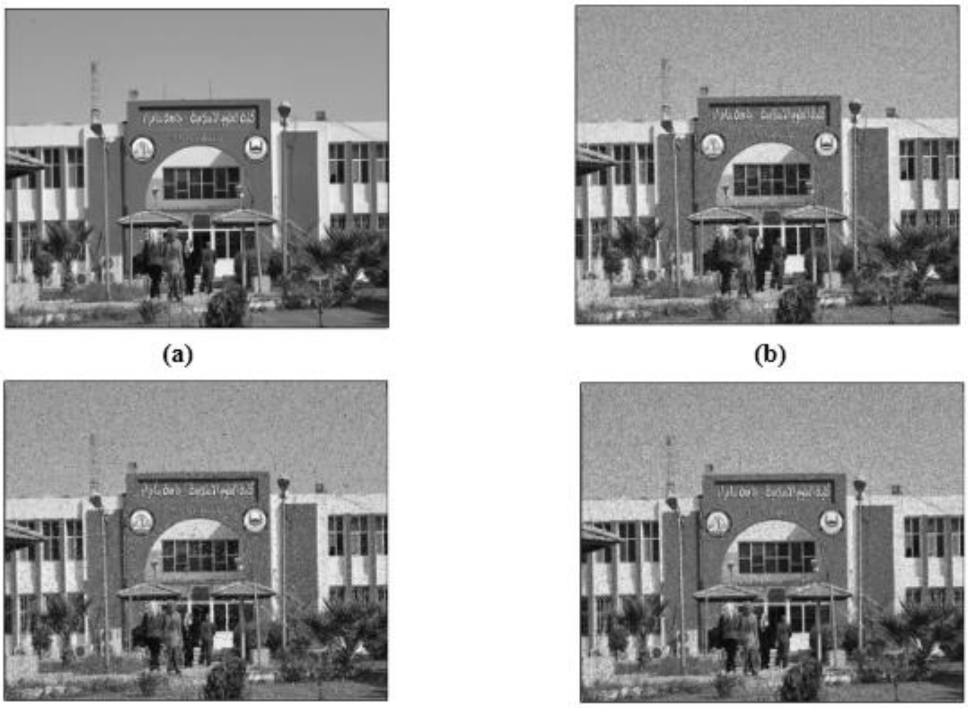


Figure (5): The proposed algorithm

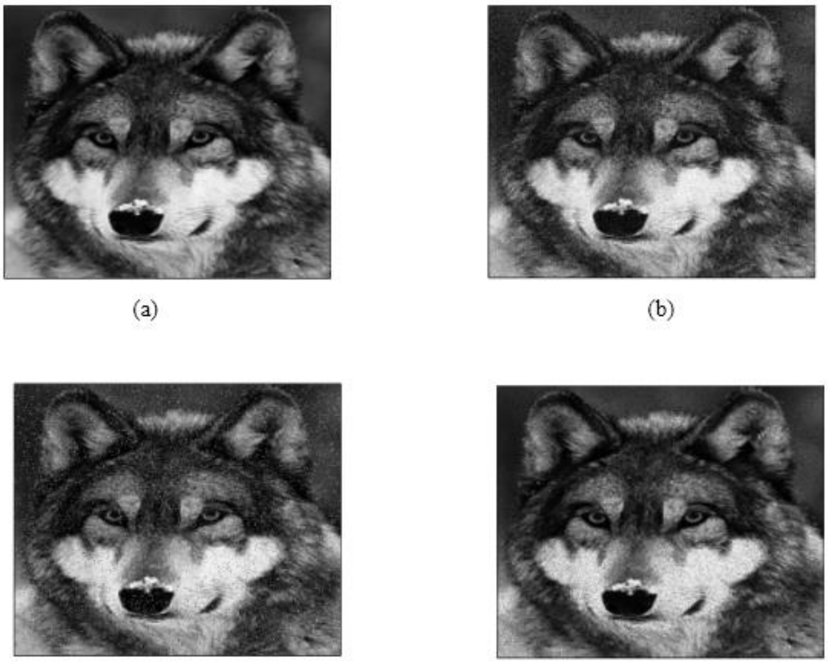
5. Results

In this section, the results obtained using the proposed algorithm is elaborated. The model shows good results by removing the noise from the images using the proposed model. Three types of noise are used salt & pepper noise, Gaussian noise and Speckle noise added to the original images of UOS and wolf grayscale image as shown in figure (6) and figure (7).



(a) (b) (c) (d)

Figure (6): (a) Original UOS (b) Gaussian (c) Salt & pepper (d) Speckle



(a) (b)

(c) (d)

Figure (7): (a) Original wolf (b) Gaussian (c) Salt & pepper (d) Speckle

The following step is to remove the noise form the noisy images recently distorted of the three types Gaussian, salt & pepper and speckle respectively, for both images UOS and wolf by using the proposed method, see figure (8) and figure (9).

(a) (b) (c)

Figure (8): (a) De-noised Gaussian (b) De-noised Salt & pepper (c) De-noised Speckle

(a) (b) (c)

Figure (9): (a) De-noised Gaussian (b) De-noised Salt & pepper (c) De-noised Speckle

In order to backing the experiment, 3 criterion exploited to estimate it, the criterion are a peak signal to noise ratio (PSNR), mean squared error (MSE) and the structural similarity index (SSIM). MSE calculate the average of the squares of the errors, including the variation of source image (original) and target image (noisy) and formulated as:

$$MSE = \frac{1}{x\,y}\sum_{a=0}^{x-1}\sum_{b=0}^{y-1}[d(a,b)-e(a,b)]^2 \quad \ldots (10)$$

PSNR is the ratio between power of maximum pixel value in an image and the mean squared error as:

$$PSNR = 10\,log_{10}\left(\frac{MAX_S^2}{MSE}\right) \quad \dots (11)$$

Also SSIM gives a ratio similarity between source image and target image, the nearest value to "1" gives the better results and it can be expressed as:

$$SSIM(a,b) = \frac{(2\mu_a\mu_{yb}+x_1)+(2\sigma_{ab}+x_2)}{(\mu_a^2+\mu_b^2+x_1)+(\sigma_a^2+\sigma_b^2+x_2)} \quad \dots (12)$$

Hard threshold is chosen based on the signal energy and noise variance while soft threshold is chosen over hard threshold. Dual tree complex wavelet transform (DTCWT) is used as wavelet filter due its nearly shift invariant and directionally selective in two and higher dimensions.

Also a comparison is made between our algorithm and traditional wavelet using hard or soft thresholding. Table (1) below shows the result of these three measures.

Table (1): MSE, PSNR, SSIM values of the de-noised images using the proposed algorithm with a comparison of traditional wavelet using hard or soft thresholding

Noisetype	Image name	Proposed algorithm			Hard thresholding			Soft thresholding		
		MSE	PSNR in dB	SSIM	MSE	PSNR in dB	SSIM	MSE	PSNR in dB	SSIM
Gaussian	UOS	18.73	35.43	0.8834	32.19	30.98	0.6216	33.11	32.96	0.7601
	Wolf	15.93	36.14	0.8940	32.34	31.89	0.7005	25.67	34.07	0.8066
Salt and pepper	UOS	24.57	34.26	0.8677	34.67	32.40	0.6436	33.08	31.82	0.6917
	Wolf	21.67	34.80	0.8893	31.80	33.14	0.6847	30.07	32.71	0.7077
Speckle	UOS	30.10	32.10	0.8974	39.64	29.73	0.6075	43.57	31.21	0.7770
	Wolf	30.92	33.26	0.9036	39.27	32.22	0.8047	41.46	31.98	0.8173

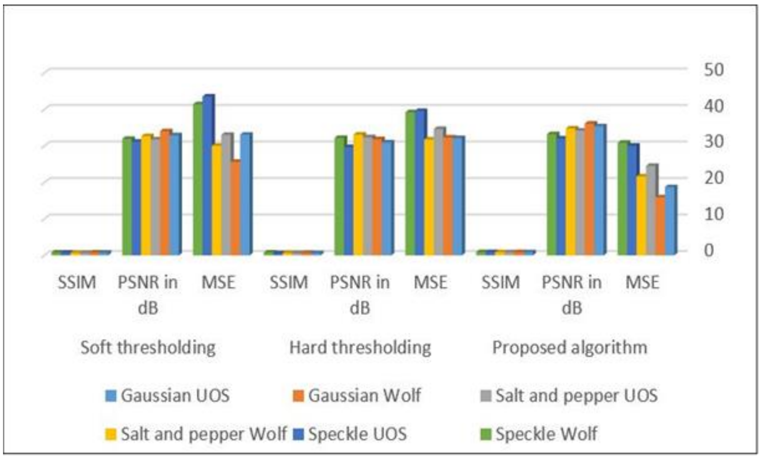


Figure (10): The results of proposed algorithm compared with traditional hard & soft thresholding

6. Conclusion

In this paper, wavelet transform and block matching accomplishes an important contribution in noise removal for images, including salt & pepper, Gaussian and speckle noise. Through the experiment, it is noticed repeating the hard thresholding in different stages in the proposed algorithm to the same image will cause blurring, hence degrading the image and that is another problem need to be solved so the researchers replaces the hard thresholding with soft thresholding. Euclidian distance is used and shows its advantage in calculating accurate distance between similar blocks. Another observation, the researchers makes is using proposed combine both hard thresholding for HH and LH coefficients and soft thresholding for LL and HL coefficients is better than using them separately. Visually, the look of the de-noised images with three types of noise used for images UOS and wolf is very close to the original ones and a demonstration for this is SSIM in table (1) which provide a good values in the case wolf image for Gaussian, salt & pepper and speckle noise the matching between original image and de-noised one is about 89%, 88% and 90% respectively, whereas in UOS image the matching between original image and de-noised one is about 88%, 86% and 89% respectively for the same kind of noise.

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ازالة ضوضاء الصورة الرقمية بالاعتماد على تحويل المويجات و تطابق الكتل

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الملخص

هذا البحث يقترح خوارزمية للتخلص من ضوضاء الصورة الرقمية ذات التدرج الرمادي ، طالما ان الصورة التي تحتوي على الضوضاء لا تعطي المنظر المطلوب لتفاصيلها فإن عملية ازالة الضوضاء تكون مطلوبة. تعتمد الخوارزمية على تحويل المويجات (wavelet transformation) و مطابقة الكتل (block matching). تم الاستفادة من طريقة المسافة الاقليدية المستخدمة في قياس المسافة بين الكتل (blocks) المتشابهة حيث اثبتت طريقة المسافة الاقليدية دقة في اعطاء المسافة بين الكتل المتشابهة بالاعتماد على العتبة الخفيفة (Soft thresholding). اما في تحويل المويجات فتم اقتراح استخدام دمج بين طريقة العتبة الثابتة (Hard thresholding) للنطاقات الفرعيةٍ (Sub-bands) وهي LL و HL و طريقة العتبة الخفيفة (Soft thresholding) للنطاقات الفرعيةٍ (Sub-bands) وهي HH و LH للصور التي جرت عليها عملية الانحلال مسبقاً (Decomposition). تم اختبار الطريقة المقترحة على ثلاثة انواع من الضوضاء وهي الضوضاء الغاوسي (Gaussian noise) وضوضاء الملح والفلفل (Salt & pepper noise) وضوضاء البقع (Speckle noise) إذ تم تقييم اداء الخوارزمية المقترحة باستخدام ثلاثة قياسات و هي خطأ تربيعي متوسط (MSE) و ذروة نسبة الإشارة إلى الضوضاء (PSNR) والتشابه الهيكلي (SSIM). اخيراً اجريت مقارنة بين الخوارزمية المقترحة و الطريقة التقليدية المتبعة في تحويل المويجات (Wavelets transform) باستخدام اما طريقة العتبة الثابتة (Hard thresholding) او طريقة العتبة الخفيفة (Soft thresholding).

الكلمات المفتاحية: تحويل المويجات ، مطابقة الكتل ، العتبة الثابتة ، العتبة الخفيفة.