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A comparative study of decomposition level using entropy and wiener function in wavelet transform

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Abstract

The fundamental requirement of applying wavelet transform on an image is to select the wavelet family and decomposition level. The selection of the wavelet family depends on the nature of the application and properties of the image/ signal. The selection of the decomposition level depends on the availability of fine details at the next level. Earlier the wavelet decomposition level was selected manually but in the recent times, there are various parameters introduced using which the level of decomposition is decided. Out of them entropy and wiener cost function are the efficient metrics for this purpose as they analyses the texture and noise level of the image respectively. This paper shows the comparative study of deciding level of wavelet decomposition using entropy and wiener cost function. The entropy metric decomposes the image on the basis of texture analysis and wiener function decomposes the image on the basis of the power of the additive noise present in the image.

Keywords: *Entropy, Wiener, DWT and Decomposition level.*

1 Introduction

The wavelet transform is one of the most widely used transform in various applications of image processing. Image storage, enhancement, restoration, transmission, compression are various fields of image processing where the wavelet transform is prevalent. The adaptive and diverse nature of wavelet transform makes it highly established and dominant in the scientific and research field.

The transform of the image or signal is one form of representing the signal or image. The wavelet transform is based on the multi-resolution analysis where the input image is decomposed into different frequency components [1]. The Fourier transform also decomposes signals into basis functions like sines and cosines. Therefore, in order to analyse the local characteristics of the input image, such as edges the Fourier transform is not capable of doing so [1]. Hence wavelet transform is used to analyse such local properties of the signal or image. The wavelets are mainly used for image compression and denoising [2]. There are certain common parameters over which most of the wavelet transforms depends on [3]. These common parameters are wavelet family and decomposition level [10]. The wavelet toolbox software contains a huge number of wavelets that can be used for continuous and discrete analysis [4]. The selection of wavelet family is decided by the properties of signal or image and the nature of the application [4]. If one understands the properties of the analysis and synthesis wavelet, then the wavelet family can be selected that is optimized for a particular application [4]. The decomposition level is a strictly positive integer that goes from level to one to two and so on as per need of the application. The subband of the first decomposition level doesn't contain fine details like edges at all in sufficiently smooth images/signals. In noisy images or signal, the subbands of the first decomposition level contain edges, but due to noise it hard to recognize them, while the subsequent levels will contain more and more useful information and less noise [10]. Commonly many decomposition levels permit to analyse and process image or signal structures of different scales, which can be critical in some applications [6].

P.-L. Shui et. al [11] in 2007 proposed new wiener cost function, to evaluate the best wavelet decomposition level in image denoising. The proposed procedure shows improvement in the

denoising performance in the highly textured images. Ana M et. al [12] in 2009 explained the optimum selection of decomposition levels in wavelet transform used for both HF and LF filtering of ECG signal on the basis of investigation of interdependency between them. Krishna Kumar et. al [1] in 2012 proposed an approach for selecting a appropriate orthogonal wavelet and optimal decomposition level for image denoising in digital wireless communication. Lei Lei et. al [5] in 2013 proposed a computational efficient method to exploit sparseness of the transformed signals to determine the appropriate decomposition level with application to ECG signal processing. The experimental result shows that the sparseness of transformed signals after DWT increases with the increasing decomposition levels. John M. Libert et. al [9] in 2013 studied the total of decomposition levels that have impact on the computational actions of image fidelity with respect to source and non-compressed images. Pandian R et. al [7] in 2016 proposed a method for high compression ratio of images. Here, the decomposition level decides the effective compression algorithm using compression ratios and PSNR values. Prabhishek Singh et. al [13] in 2018 proposed a wavelet based SAR image despeckling technique using method noise thresholding and local correlation. They used 2D-DWT for this purpose. They proposed a new way choosing decomposition level using entropy metric by deriving a new formula for maximum information retrieval.
The paper addresses method of selection of level of decomposition in wavelet transform (2D-DWT) in the field of image denoising. As per literature the image decomposition is performed from level 1-7 but in most of the cases the best results are obtained from level 3-5. There is a scope of improvement in this methodology for more detail preservation. The paper introduces and compares the two parameters used for selection of decomposition level i.e. entropy and wiener function in wavelet transform. The section 2 describes the metrics used for wavelet decomposition level i.e. entropy and wiener function. The section 3 compares these two metrics using experimental testing and section 4 concludes the paper.

2 Wavelet Decomposition Level

The wavelets are frequently castoff to denoise the 2D-signals, such as images. There are two steps required to perform wavelet transform (2D-DWT). The first step is to select a wavelet type, and second step is to decide the level of decomposition [14]. The selection of the wavelet type or wavelet family depends on the nature of the application and the properties of the image. Depending on these factors the wavelet family is selected [15]. The selection of decomposition level is another input requirement of the wavelet transform. In the beginning of the research in wavelets, the decomposition level was chosen manually [21]. It was tested from level 1 to 7 and the results were checked at all these levels. The level at which the results were obtained best, that level is decided as the decomposition level of that application. Later in the previous years, there are some parameters introduced for the selection of the wavelet decomposition level i.e. variance, mean, standard deviation and many more [19]. Out of them entropy and wiener are the two most useful parameters used for wavelet decomposition because entropy analyses the texture of the image and depending upon the availability of the information, it decides the decomposition level and wiener function relies on both sparseness of image and noise variance [13], [20], [24]. The below subsections describes the method of selecting the wavelet decomposition level using entropy and wiener functions.

2.1 Entropy Function

The 2D-DWT is applied on the input noisy image. The input image is transformed into two parts i.e. approximate part and detailed part. The detailed part contains the horizontal (HL1), vertical (LH1) and diagonal (HH1) information of the image and approximate part (LL1) contains the rest approximate information of the image [17], [22]. If the sufficient information is obtained from the HL1, LH1 and HH1 then LL1 is further not decomposed but if the sufficient information is not obtained from the HL1, LH1 and HH1 then LL1 is further decomposed into LL2, LH2, HL2 and HH2 [17]. The entropy is a useful metric in deciding the number of decomposition levels required for the wavelet decomposition. The entropy measures the uncertainty of intensity values that demonstrate the texture of the image [16]. For every next decomposition level (n), the entropy is calculated for the approximate component of the parent and child node [23]. The higher value of entropy of child node than the parent node specifies the existence of information in the approximate part at the next upper level. This needs next decomposition. This procedure stays till the described condition gets failed. Entropy is formulated as,

$$\text{Entropy} = -\sum_{i} P_i \text{Log}_2 P_i \tag{1}$$

The following steps explain the process of wavelet decomposition up to level n using entropy metric:

1. Perform 2D-DWT on the image up to level 2 that decomposes the image into LL1, HL1, LH1 and HH1 for the first level decomposition and LL2, HL2, LH2 and HH2 for the second level decomposition.
2. Compute the entropy of approximate part of parent node i.e. LL1 and child node i.e. LL2 using Eq (1) and then check the below condition:
   if (Entropy(child node) > Entropy (parent node)), then go for next decomposition level.
   if (Entropy(child node) ≤ Entropy (parent node)), then stop decomposing the image.

2.2 Wiener Function

The noise level i.e. additive noise power estimated by the wiener function can efficiently decides the wavelet decomposition level [13]. The wavelet decomposition is performed to obtain the maximum information from the image. But on performing more decomposition, the degradation increases. So it is crucial to decide where to stop while performing decomposition. In this case, the estimated noise level can easily decide the level of decomposition. The selection of level of decomposition is manual process using wiener function by noise level. The following function decides the decomposition level:

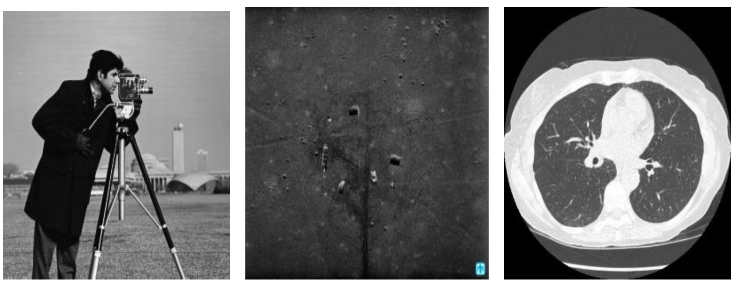
1. Perform 2D-DWT on the image and set maximum number of level. Let the decomposed components of the image are LL1, HL1, LH1 and HH1 for the first level decomposition and LL2, HL2, LH2 and HH2 for the second level decomposition.
2. Apply the wiener cost function on the approximate part of parent node i.e. LL1 and child node i.e. LL2 and check the noise level of approximate part of parent node i.e. LL1 and child node i.e. LL2 and depending on the below condition of the noise level, perform the wavelet decomposition:
   if(noise_level(child node) ≈ noise_level(parent node)), then go for next decomposition level.
   if(noise_level(child node) >> noise_level(parent node)), then stop decomposing the image.

Note: "≈" denotes approximately equal to and ">>" denotes much greater than.

The step 2 is performed manually up to set maximum levels and until the above condition meets, the decomposition goes on and when it fails, removes the remaining child nodes.

3 Comparative Study

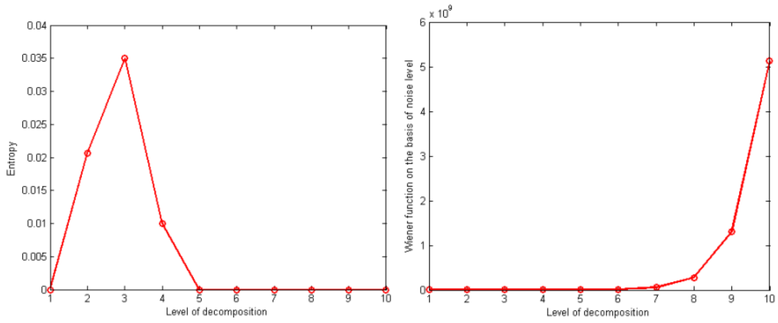
The experimental evaluation is performed on three different kinds of images i.e. classical image, SAR image and medical image. The Fig. 1 shows the image dataset over which the experimental evaluation is done. The Fig. 1(a) is cameraman image available in the Matlab toolbox. Fig. 1(b) and 1(c) are the SAR image and CT scan image available at open public access database i.e. [18] and [25] respectively.



(a) (b) (c)

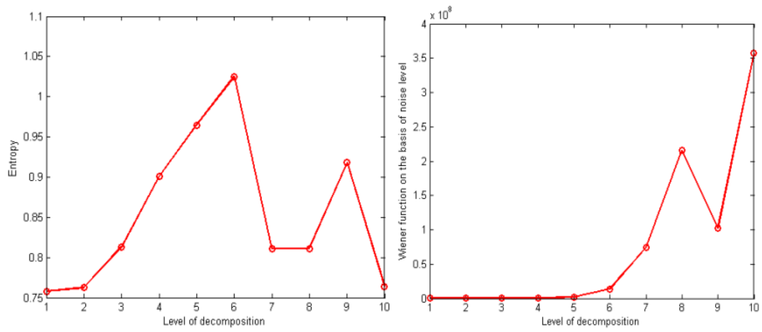
Fig. 1. Image Dataset

The Fig. 2, 3 and 4 shows the graph for selecting the level of decomposition using entropy function and wiener function on the basis of noise level. In the graphs, the X axis shows the level of decomposition and Y axis shows the entropy value and noise level by wiener function.



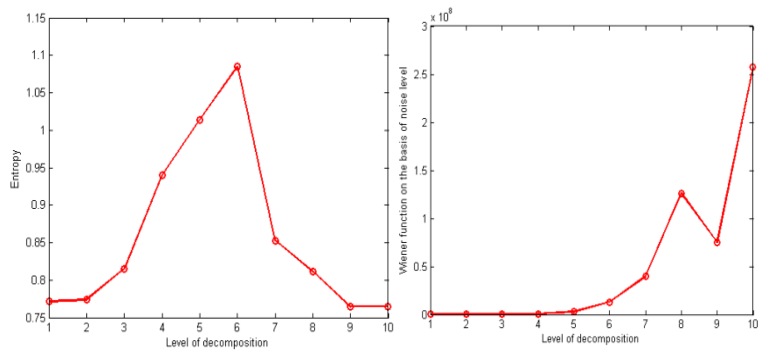
(a) (b)

Fig. 2. Selecting decomposition level of Fig. 1(a) using (a) entropy and (b) wiener on the basis of noise level



(a) (b)

Fig. 3. Selecting decomposition level of Fig. 1(b) using (a) entropy and (b) wiener on the basis of noise level



(a) (b)

Fig. 4. Selecting decomposition level of Fig. 1(c) using (a) entropy and (b) wiener on the basis of noise level

The experiment is performed on large dataset of images and it is observed that on using the entropy metric, the entropy value of the next decomposition level increases up to certain point but after some level it start decreasing as shown in the Fig. 2(a), 3(a) and 4(a). This indicates the loss of information or non-availability of fine details which simple indicates to stop decomposing the image. On the other hand, the decomposition performed using wiener function on the basis of noise level is shown in the Fig. 2(b), 3(b) and 4(b). Since the wiener function depends on two properties i.e. sparseness of image representation and noise level. So there are multiple ways of using the wiener function for wavelet decomposition. But out of them using noise level is one of the most easiest and efficient method for deciding the wavelet decomposition. It estimates the power of additive noise at each decomposition. Depending on this noise level, the level of decomposition is decided. As per Fig. 2, 3 and 4, the number of level of wavelet decomposition needed is shown in the Table 1.

Table 1. Number of wavelet decomposition levels required for Fig. 1 using entropy and wiener function

Image Dataset	Number of level of wavelet decomposition using	
	Entropy function	Wiener function on the basis of noise level
Fig. 1(a)	3	6
Fig. 1(b)	6	5
Fig. 1(c)	6	5

4 Conclusion and Future Scope

The article shows the selection of level of decomposition using entropy and wiener function on the basis of noise level. A comparative study is performed between them. The authors have proposed a way of automatically selecting the level of decomposition. The entropy and wiener function are experimented on the approximate component of the dataset images because approximate part decomposes in the further processing. The experimental analysis and evaluation is performed on three different kinds of images like optical image (cameraman), SAR image and CT scan image. This testing shows the adaptive nature of entropy and wiener function which can be used with wavelet transform in any application of the image processing.

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