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Original research article

A comparative study on wavelet denoising for high noisy CT images of COVID-19 disease

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ABSTRACT

Coronavirus disease (COVID-19), detected in Wuhan City, Hubei Province, China, is a pandemic disease and affecting all people in the world. Real-time reverse transcription polymerase chain reaction (RT-PCR) test is the standard clinical tool for the diagnosis of COVID-19. Computed Tomography (CT) is an alternative method to RT-PCR test for the diagnosis of COVID-19 due to some disadvantages of the RT-PCR test. In this method, the target is to determine coronavirus pneumonia from CT images. However, high noise decreases the image quality, so a noise reduction filter is used. The wavelet functions are widely used to reduce noise in images. In this study, a performance comparison of the different wavelet functions in CT image denoising is proposed. Significant remarks are obtained from the analysis to improve the quality for CT exams of COVID-19 disease.

1. Introduction

Coronavirus disease (COVID-19) is a highly contagious disease and detected in December 2019 in Wuhan City, Hubei Province, China [1]. There have been about 98 million confirmed cases of COVID-19, including more than 2 million deaths, reported to World Health Organization (WHO) in late January 2021 [2]. Despite the measures such as social distance and increased hygiene awareness, the virus is spreading rapidly today. The patients with COVID-19 have some clinical symptoms such as fever, dyspnea, dry cough, and bilateral lung infiltrates on imaging [3] and the symptomatic patients should be tested for diagnosis of the disease.

The RT-PCR test is a real-time reverse transcription polymerase chain reaction test and widely used in the diagnosis of COVID-19 disease. However, RT-PCR test kits are limited, and results are not available immediately [4]. According to [5,6], the sensitivity of Computed Tomography (CT) is greater than that of the RT-PCR test, thus CT may be used as an alternative to the RT-PCR test. Chest CT is used both to determine whether the patient has COVID-19 and to evaluate the lung when the COVID-19 test is positive [7].

There are many proposed techniques to diagnose the patient infected with COVID-19 from CT images. Each proposed technique has its own merits and limitations. The noise in the CT image limits the success of the technique used to diagnose the disease. The noise in the CT image is affected by many sources. Some majors are random noise, statistical noise, electronic noise, and roundoff errors [8]. The noise in CT images can be characterized using additive white Gaussian noise (AWGN) [9–11]. Too much noise causes poor image quality, thus especially high noisy CT images require a filter for noise reduction. The goal of image denoising is to reduce the noise in the CT image while preserving the image features.

The wavelet thresholding method has been widely used to reduce the noise in the image since wavelet transform provides a not uniform decomposition of the image in space-frequency domain. One of the problems in the wavelet thresholding method is to find the...
optimal threshold. The threshold value is used to distinguish useful details in the image from the noise. The choice of wavelet function is also an important issue because each function has different properties affecting the wavelet thresholding method. There is a wide range of literature on selecting the wavelet functions in image processing [12–14].

In this study, a performance comparison of the different wavelet functions is proposed to reduce high noise for COVID-19 CT images. Based on the results, a proper wavelet function can be selected to obtain optimum performance for COVID-19 disease.

2. Wavelet thresholding method

The wavelet thresholding method has been widely used in noisy images to reduce the noise. The first step in this method is discrete wavelet transform (DWT). DWT decomposes an image into subbands with different coefficients: LL, HH, HL, and LH as shown in Fig. 1. While the coefficient of subband LL is called approximation coefficients, the coefficients of subbands HH, HL, and LH are called detail coefficients. These coefficients have either noise or important signal features. Small coefficients are mostly caused by noise, while large coefficients are caused by important signal features. The wavelet thresholding algorithm filters only small coefficients in the HH, HL, and LH subbands using a threshold function. There are two types of thresholding procedures, soft-thresholding and hard-thresholding. The soft-thresholding procedure sets the wavelet coefficients less than or equal to threshold T to zero and shrinks the coefficients greater than threshold T toward zero by the threshold T. The difference between the soft and hard thresholding procedures is that the hard thresholding procedure keeps the wavelet coefficients greater than the threshold T. There are different shrinkage methods to determine the threshold T, VisuShrink [15] and BayesShrink [16]. VisuShrink provides a threshold value for an image, while BayesShrink provides a threshold value for each detail subband. After filtering the wavelet coefficients, inverse discrete wavelet transform (IDWT) is used to obtain the filtered image.

3. Materials and metrics

In this work, we apply the wavelet thresholding algorithm to the high noisy CT images and evaluate the performance of each wavelet function with image quality metrics. We obtain the images from Italian Society of Medical and Interventional Radiology (SIRM) COVID-19 database [17]. SIRM COVID-19 database reports COVID-19 radiographic images with varying resolutions and is used in the literature [18]. Twenty CT images are obtained from this database. These images are in the RGB format and they are converted to gray-scale format using the image processing toolbox of MATLAB [19].

The gray level images obtained are used as reference images, some of them are shown in Fig. 2.

Each reference image is corrupted by AWGN. The noise levels of sigma (σ) = 30, 50 are selected to comply with the previous studies [20,21]. After high noisy images are obtained, different wavelet functions are used to filter the obtained high noisy images. After filtering the high noisy CT images, the filtered images must be evaluated with quality metrics. The first quality metric is the beta metric (β) [22] used in this paper, defined by:

\[
β = \frac{\Gamma(\Delta I - \Delta \hat{I}, \Delta \hat{I} - \Delta \hat{I})}{\sqrt{\Gamma(\Delta I - \Delta \hat{I}, \Delta \hat{I} - \Delta \hat{I}) \Gamma(\Delta \hat{I} - \Delta \hat{I}, \Delta \hat{I} - \Delta \hat{I})}}.
\]

where \( I \) is the reference image, \( \hat{I} \) is the filtered image, \( \Delta I \) and \( \Delta \hat{I} \) are the high pass filtered version of \( I(i,j) \) and \( \hat{I}(i,j) \), \( \Delta \hat{I} \) and \( \Delta \hat{I} \) are the

| LL \_3 | HL \_3 | HL \_2 | HL \_1 |
|-------|-------|-------|-------|
| LH \_3 | HH \_3 |       |       |
|       |       | LH \_2 | HH \_2 |
|       |       |       |       |
|       |       |       |       |
|       |       |       |       |

Fig. 1. Subbands of an image after DWT.
mean intensities of $\Delta I$ and $\Delta \hat{I}$, respectively. $\beta$ indicates the edge preservation performance of the filter. This value is between 0 and 1, where values nearer to 1 indicate higher image quality.

Additionally, the Peak Signal-to-Noise Ratio (PSNR) is used to evaluate the noise reduction performance of the filter:

$$PSNR = 10 \log_{10} \frac{P^2}{\frac{1}{mn} \sum_{i=1}^{n} \sum_{j=1}^{m} [I(i,j) - I_f(i,j)]^2}$$

(2)

where $P$ is the maximum possible pixel value of the image, the number of rows and columns are $n$ and $m$ respectively, $I_f(i,j)$ is the filtered or noisy image. Higher PSNR depicts the more improved image; frequently applied image quality metric in literature.

4. Results and discussion

In this study, we apply wavelet thresholding algorithm to improve the image quality using soft thresholding procedure because soft thresholding procedure is a very popular technique and preferred to hard thresholding procedure [14]. Bayes thresholding method further improves image quality than Visu thresholding method [23], thus we use Bayes thresholding to obtain threshold value.

First, Daubechies (db), Symlet (sym), Coiflet (coif) functions are used to obtain the wavelet coefficients from the high noisy CT images. Each function has its properties such as orthogonality, symmetry, and filter order (N). An orthogonal wavelet is a wavelet whose associated wavelet transform is orthogonal and it preserves the total signal energy. Symmetry means that the wavelet and scaling functions are symmetric and filter order determines the filter length. The examined functions have the following properties [14]:

- db: orthogonality, weak symmetry, filter length $L = 2N$
- sym: orthogonality, quite symmetry, filter length $L = 2N$
- coif: orthogonality, quite symmetry, filter length $L = 6N$
The obtained PSNR and $\beta$ values of filtered and noisy images are shown in Fig. 3. For the sake of clarity, the graphs in Fig. 3 are shown in two parts for each quality index and noise level. Each part shows PSNR or $\beta$ values of noisy and ten filtered images (FI). Besides, noisy image is indicated as $n$, and the functions coif, db, and sym are indicated as c, d, and s, respectively.

Fig. 3 shows that as the noise level increases, the PSNR and $\beta$ values of noisy images decrease, as expected. The color lines show that each class of the wavelet functions offers better performance than the noisy image.

Fig. 3. The obtained PSNR and $\beta$ values of noisy and filtered images for orthogonal functions.
Table 1
The obtained PSNR and $\beta$ values using wavelet functions coif 1, db1, db2, and db 3.

| PSNR | $\beta$ |
|------|--------|
| coif1 | db1 | db2 | db3 | coif1 | db1 | db2 | db3 | coif1 | db1 | db2 | db3 | coif1 | db1 | db2 | db3 | coif1 | db1 | db2 | db3 |
| FI 1  | 30.774 | 30.205 | 31.271 | 31.669 | 0.514 | 0.456 | 0.583 | 0.539 | 27.982 | 27.062 | 28.323 | 28.520 | 0.489 | 0.325 | 0.572 | 0.544 |
| FI 2  | 26.336 | 25.408 | 26.201 | 26.417 | 0.571 | 0.454 | 0.555 | 0.603 | 23.660 | 23.011 | 23.631 | 23.801 | 0.518 | 0.392 | 0.511 | 0.556 |
| FI 3  | 27.825 | 26.896 | 27.714 | 28.042 | 0.809 | 0.643 | 0.816 | 0.845 | 24.741 | 23.970 | 24.647 | 24.940 | 0.783 | 0.571 | 0.795 | 0.829 |
| FI 4  | 28.607 | 27.773 | 28.619 | 28.844 | 0.355 | 0.243 | 0.348 | 0.442 | 25.017 | 24.455 | 25.016 | 25.157 | 0.310 | 0.188 | 0.294 | 0.389 |
| FI 5  | 31.086 | 29.509 | 31.029 | 31.361 | 0.887 | 0.682 | 0.882 | 0.917 | 27.666 | 26.769 | 27.643 | 27.839 | 0.885 | 0.668 | 0.878 | 0.915 |
| FI 6  | 25.552 | 24.973 | 25.595 | 25.771 | 0.283 | 0.254 | 0.286 | 0.311 | 22.399 | 21.878 | 22.349 | 22.531 | 0.202 | 0.169 | 0.195 | 0.221 |
| FI 7  | 25.182 | 24.631 | 25.106 | 25.335 | 0.660 | 0.583 | 0.633 | 0.675 | 22.133 | 21.783 | 21.875 | 22.129 | 0.604 | 0.519 | 0.511 | 0.583 |
| FI 8  | 25.844 | 25.164 | 25.790 | 25.986 | 0.335 | 0.257 | 0.331 | 0.376 | 23.522 | 23.019 | 23.501 | 23.628 | 0.279 | 0.199 | 0.277 | 0.316 |
| FI 9  | 25.915 | 25.298 | 25.865 | 26.027 | 0.330 | 0.245 | 0.326 | 0.364 | 23.549 | 23.090 | 23.500 | 23.605 | 0.275 | 0.193 | 0.266 | 0.302 |
| FI 10 | 25.571 | 24.819 | 25.532 | 25.762 | 0.299 | 0.216 | 0.298 | 0.347 | 23.493 | 22.902 | 23.464 | 23.634 | 0.238 | 0.160 | 0.239 | 0.280 |
| FI 11 | 28.397 | 27.675 | 28.401 | 28.664 | 0.722 | 0.529 | 0.723 | 0.791 | 25.021 | 24.598 | 25.014 | 25.136 | 0.704 | 0.502 | 0.703 | 0.769 |
| FI 12 | 27.703 | 27.687 | 27.983 | 26.042 | 0.642 | 0.480 | 0.642 | 0.690 | 25.405 | 24.578 | 25.423 | 25.659 | 0.624 | 0.449 | 0.624 | 0.673 |
| FI 13 | 25.044 | 24.488 | 24.969 | 25.163 | 0.445 | 0.394 | 0.436 | 0.467 | 22.901 | 22.279 | 22.910 | 23.022 | 0.360 | 0.274 | 0.359 | 0.388 |
| FI 14 | 24.716 | 24.330 | 24.694 | 24.859 | 0.494 | 0.472 | 0.493 | 0.518 | 22.160 | 21.677 | 22.163 | 22.284 | 0.387 | 0.334 | 0.382 | 0.408 |
| FI 15 | 27.488 | 26.758 | 27.449 | 27.600 | 0.778 | 0.683 | 0.767 | 0.780 | 25.111 | 24.554 | 25.134 | 25.166 | 0.730 | 0.620 | 0.732 | 0.706 |
| FI 16 | 28.416 | 27.06 | 28.387 | 28.755 | 0.455 | 0.270 | 0.445 | 0.537 | 25.942 | 24.982 | 25.889 | 26.186 | 0.394 | 0.235 | 0.386 | 0.474 |
| FI 17 | 30.347 | 28.609 | 30.431 | 30.751 | 0.680 | 0.397 | 0.664 | 0.748 | 26.919 | 25.630 | 26.933 | 27.157 | 0.666 | 0.379 | 0.657 | 0.739 |
| FI 18 | 28.936 | 27.618 | 28.854 | 29.189 | 0.573 | 0.377 | 0.565 | 0.636 | 26.110 | 25.203 | 26.021 | 26.303 | 0.536 | 0.346 | 0.530 | 0.609 |
| FI 19 | 28.186 | 26.738 | 28.201 | 28.540 | 0.676 | 0.449 | 0.673 | 0.757 | 25.087 | 24.101 | 25.018 | 25.344 | 0.651 | 0.425 | 0.642 | 0.727 |
| FI 20 | 28.153 | 26.936 | 28.114 | 28.380 | 0.478 | 0.307 | 0.465 | 0.536 | 25.680 | 24.838 | 25.769 | 25.860 | 0.397 | 0.246 | 0.395 | 0.467 |
Comparing the wavelet functions, it is possible to conclude: the denoising performance of the wavelet functions is fairly insensitive to symmetry for CT imaging. Comparing sym and db functions with the same filter length but with different symmetry properties, they have very similar performances in terms of both PSNR and β.

The denoising performance of the wavelet functions is more sensitive to filter length. When the results (PSNR and β values) of filtered images are analyzed for each wavelet function (coif, db, and sym) in Fig. 3, longer filters give better results for CT images. Especially, the second-order wavelet functions perform more performance than the first-order wavelet functions for each wavelet function. There is a big difference between the results of first-order and second-order wavelet functions. For the longer filter orders, the results obtained increase by decreasing the difference between the results obtained from the wavelet functions with successive filter orders. This means that the longer filter reduces noise well and provides a better edge preservation performance.

However, the longer the filter, the longer the processing time. If processing time is important, a smaller filter order can be preferred for denoising. The smallest filter order of the wavelet function coif is one, and the corresponding filter length is six. Besides, the smallest filter order of the wavelet function db is one and the corresponding filter length is two. As shown in Table 1, comparing the performance of the function coif1 and functions db1, db2, and db3 (the function coif1 and the function db3 have equal filter length), it is possible to make the following conclusions:

(i) the function coif1 generally performs better than the function db1.
(ii) the function coif1 has approximately the same results as the function db2.
(iii) comparing the functions coif1 and db3, the function db3 generally gives better results than the function coif1.

It is necessary to strike a balance between processing time and denoising performance. Therefore, when the processing time is important, the db or sym function (db1, db2, and db3 give the same results with sym1, sym2, and sym3, respectively) can be used.

### Table 2

Comparing the obtained maximum values using the orthogonal and biorthogonal functions.

| FI  | σ = 30 | σ = 50 |
|-----|-------|-------|
|     | PSNR  | β     | PSNR  | β     |
|     |       |       |       |       |
| FI 1| Orthogonal function | 32.023 | 0.671 | 28.699 | 0.657 |
|     | Biorthogonal function | 31.838 | 0.657 | 28.384 | 0.590 |
| FI 2| Orthogonal function | 26.688 | 0.637 | 23.916 | 0.585 |
|     | Biorthogonal function | 26.605 | 0.630 | 23.720 | 0.551 |
| FI 3| Orthogonal function | 28.191 | 0.861 | 24.988 | 0.842 |
|     | Biorthogonal function | 27.994 | 0.847 | 24.706 | 0.837 |
| FI 4| Orthogonal function | 29.078 | 0.488 | 25.279 | 0.439 |
|     | Biorthogonal function | 28.836 | 0.402 | 24.961 | 0.250 |
| FI 5| Orthogonal function | 31.564 | 0.926 | 27.980 | 0.924 |
|     | Biorthogonal function | 31.535 | 0.926 | 27.675 | 0.926 |
| FI 6| Orthogonal function | 26.128 | 0.350 | 22.793 | 0.300 |
|     | Biorthogonal function | 25.453 | 0.280 | 22.245 | 0.191 |
| FI 7| Orthogonal function | 25.685 | 0.752 | 22.378 | 0.727 |
|     | Biorthogonal function | 25.042 | 0.733 | 21.905 | 0.598 |
| FI 8| Orthogonal function | 26.100 | 0.401 | 23.743 | 0.337 |
|     | Biorthogonal function | 26.035 | 0.397 | 23.515 | 0.297 |
| FI 9| Orthogonal function | 26.035 | 0.385 | 23.509 | 0.288 |
|     | Biorthogonal function | 25.922 | 0.378 | 23.742 | 0.365 |
| FI 10| Biorthogonal function | 25.909 | 0.384 | 23.647 | 0.287 |
|   | Orthogonal function | 28.983 | 0.824 | 25.234 | 0.798 |
|   | Biorthogonal function | 28.784 | 0.796 | 24.915 | 0.792 |
| FI 12| Orthogonal function | 28.296 | 0.715 | 25.895 | 0.696 |
|    | Biorthogonal function | 28.276 | 0.703 | 25.677 | 0.683 |
| FI 13| Orthogonal function | 25.333 | 0.490 | 23.204 | 0.422 |
|     | Biorthogonal function | 25.274 | 0.495 | 23.040 | 0.404 |
| FI 14| Orthogonal function | 25.006 | 0.532 | 22.441 | 0.446 |
|     | Biorthogonal function | 24.909 | 0.534 | 22.307 | 0.432 |
| FI 15| Orthogonal function | 27.824 | 0.813 | 25.441 | 0.769 |
|     | Biorthogonal function | 27.581 | 0.804 | 25.030 | 0.746 |
| FI 16| Orthogonal function | 29.119 | 0.656 | 26.331 | 0.600 |
|     | Biorthogonal function | 28.756 | 0.598 | 26.194 | 0.482 |
| FI 17| Orthogonal function | 31.279 | 0.835 | 27.429 | 0.818 |
|     | Biorthogonal function | 30.805 | 0.804 | 26.925 | 0.787 |
| FI 18| Orthogonal function | 29.540 | 0.723 | 26.562 | 0.689 |
|     | Biorthogonal function | 29.118 | 0.683 | 26.204 | 0.634 |
| FI 19| Orthogonal function | 28.795 | 0.807 | 25.612 | 0.785 |
|     | Biorthogonal function | 28.879 | 0.795 | 25.370 | 0.756 |
| FI 20| Orthogonal function | 28.808 | 0.650 | 26.137 | 0.546 |
|     | Biorthogonal function | 28.470 | 0.589 | 25.855 | 0.456 |
instead of the coif function. If the processing time is not important, when the functions with longer filter length shown in Fig. 3 are compared, the results obtained from the functions are very close to each other. Thus, we can conclude from Fig. 3 and Table 1 that sym or db function should be preferred to coif function to reduce the noise in CT image for COVID-19 disease.

After the orthogonal functions, the biorthogonal functions are evaluated to find the proper wavelet function for CT imaging of COVID-19. These non-orthogonal functions are symmetric and use two different functions to analyze and to synthesize signals. The high noisy CT images employed for orthogonal functions are used to evaluate the biorthogonal functions. The biorthogonal functions used in this paper are bior1.1, bior1.3, bior1.5, bior2.2, bior2.4, bior2.6, bior2.8, bior3.1, bior3.3, bior3.5, bior3.9, bior4.4, bior5.5 and bior6.8. Table 2 shows the maximum PSNR and \( \beta \) values obtained from orthogonal and biorthogonal functions for each filtered image and noise level. According to Table 2, either the orthogonal and the biorthogonal functions have similar results, or the orthogonal function has better results than the biorthogonal function. Then, it can be concluded that the orthogonal function has a better edge preservation performance while reducing noise better in high noisy CT images than the biorthogonal function.

5. Conclusions

In this paper, a comparative study on wavelet denoising for high noisy CT images of COVID-19 disease is presented. The effect of choosing different wavelet functions each with its properties of orthogonality, filter order, and symmetry is investigated. The obtained results show: (i) the orthogonal functions have better performance than the biorthogonal functions, (ii) db and sym functions have similar results, (iii) the wavelet functions with higher filter length are more effective to de-noise very noisy CT images, (iv) the function db3 or sym3 gives better results than the function coif1 (the functions db3 and coif1 have equal filter length). Therefore, if the processing time is important, the function db or sym should be used instead of the function coif, (v) if the processing time is not important, the functions have similar results for the longer filter lengths. Thus, sym or db function can be preferred to coif function to reduce the noise in CT image for COVID-19 disease.

Today, CT is an alternative method to the RT-PCR test for the diagnosis of COVID-19. In the future, CT will be used to assess the lung to monitor the impact of COVID-19, even if the COVID-19 disease is reduced or gone. We recommend a comparative study of wavelet functions and their properties to provide a useful guideline for improving the quality of CT images.

Declaration of Competing Interest

The authors report no declarations of interest.

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