Noise Reduction on Received Signals in Wireless Ultraviolet Communications Using Wavelet Transform

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ABSTRACT In wireless ultraviolet optical communications, noise is one of the most essential factors affecting the communication system performance. This paper presents a scheme of reducing noise in the received ultraviolet signal using wavelet transform algorithms. An effective signal-to-noise ratio (SNR) calculation method for the received signals is also proposed, and adopted by our wavelet denoising scheme so that an optimal wavelet basis function can be selected. The proposed denoising method is applied to both the ultraviolet signals generated from the multi-scattering transmission simulation model and the signals received from physical experiments, under different conditions of transceiver elevation angles and communication distances. The results show consistently that the wavelet transform algorithm can significantly improve the SNRs at the receiving end. When the wavelet basis is $\text{coif}2$, the best denoising effect is achieved where the improved SNR reaches 11.9925 dB on average for various physical conditions.

INDEX TERMS Ultraviolet optical communication, scattering transmission, wavelet transform, signal-to-noise ratio, signal denoising.

I. INTRODUCTION Ultraviolet Communication (UVC) is a new type of wireless optical communication method \cite{1}, \cite{2}. Ultraviolet (UV) rays with wavelength between 200~280nm in the solar blind zone are used as carriers of information transmission. Signals are transmitted through the scattering of UV by atmospheric particles, aerosols, and dust in the atmosphere. For this reason, UVC can realize non-line-of-sight (NLOS) optical communications \cite{3} and avoid the shortcomings of traditional line-of-sight (LOS) communications. Also, UVC has the advantages of high confidentiality and strong anti-interference ability, and can work in all-weather conditions. These features enable the wireless UVC to work well in complex terrain environments \cite{4}, and to have broad application prospects in the field of covert communications \cite{5}--\cite{7}.

At present, most of the research work related to UVC systems focuses on establishing UVC channel models \cite{8}, \cite{9}, studying channel characteristics \cite{10}, examining noise components, and exploring signal-to-noise (SNR) estimation methods. In UVC systems, noise can cause serious interference to signal; therefore, extensive research has been conducted on noise-related issues to improve communication performance. Authors in \cite{11} studied the SNR and the bit error rate (BER) in LOS and NLOS wireless UV links, and presented a SNR-estimation method for UVC systems. Background noise in UVC channels is studied in \cite{12} using the Monte Carlo (MC) simulation method. Reference \cite{13} developed a multiple-input multiple-output (MIMO) receiver system to suppress shot noise. Manchester coding was adopted to suppress the optical background noise in a LED wireless communication system \cite{14}. A SNR estimation method suitable for NLOS UV communications was proposed in \cite{15} to estimate the channel capacity. Reference \cite{16} studied the influence of mutual crosstalk between impulse response sequences on the communication rate. In order to analyze the channel capacity, the SNR of a NLOS non-coplanar UV system was studied using the quantum limit method \cite{17}. In the same year researchers \cite{18} proposed the use of anti-multipath UV multiple access technology to solve the problem of signal
interference when the signal reaches the receiver through multipath transmission. Reference [19] designed and implemented a digital filter on FPGA to suppress noise at the receiver end. As a result, the overall error performance of the system was improved, but the filter design was complicated and the workload was relatively large.

In a UVC system, the received signal is often in a small signal state, and the signal amplitude is low. If we don’t perform noise reduction, the signal will be submerged in the noise. Therefore, noise reduction is of great significance for improving the performance of a UVC system. Many denoising techniques have been studied in the literature, including Fourier transform, short-time Fourier transform [20], wavelet transform [21], low-rank approximation approach [22], empirical mode decomposition (EMD), and bi-dimensional EMD (BEMD) [23]. The Fourier transform can realize spectrum analysis, yet does not have time domain information, so the signal denoising effect is not effective [24]. The short-time Fourier transform adds a time window to the Fourier transform to achieve time-frequency analysis, but the window size cannot be changed, so it is a single-resolution signal analysis method. The EMD method adaptively decomposes a signal into several intrinsic mode functions (IMFs), and the noise is removed by filtering out noisy IMFs [25], [26], whereas it has mode mixing problem which causes serious aliasing in the time-frequency distribution. The BEMD algorithm is an extension of EMD algorithm, and is more applicable to non-linear and complex signal analyses. This method is simple, but ignores a small amount of detailed information containing in the low-frequency IMFs. The low-rank (LR) approximation approach in [22] computes the best LR approximation of a formulated Hankel matrix and then obtain the denoised data from the LR matrix. However, without utilizing the Hankel structure when computing the LR approximation, if we rearrange the denoised data into a Hankel matrix, it is in general not exactly LR as expected. The Wavelet transform (WT) is extensively employed in signal denoising due to its multi-resolution, low entropy, and decorrelation [27]–[29]. It can be used to identify noise in signals and suppress high frequency noise before reconstructing the signal. Denoising algorithms based on wavelet analysis are generally superior to traditional denoising algorithms.

The wavelet analysis involves selection of a suitable decomposition level and wavelet basis functions. A new method is proposed in [30] to choose wavelet functions and levels of decomposition. Reference [31] uses the minimum squared error (MSE) and SNR to estimate an optimum set of WT parameters for electroencephalogram (EEG) signal denoising, where the parameters include mother wavelet function, decomposition level, and thresholding function. Five powerful metaheuristic algorithms were proposed to find the optimal WT parameters for EEG signal denoising in [32]. Reference [33] proposed an index that combines the effects of root-mean-square error, SNR, correlation coefficient, and smoothness, to determine an optimal decomposition layer. However, these four denoising-quality indexes all have their own defects. Only when the true value of the signal is known, can these four indexes truly evaluate the effect of wavelet denoising. Among the four indexes, SNR is an important index for judging the communication quality of UVC systems; however, the SNR at the receiver of UVC systems is often calculated by the quantum limit SNR formula [34], which is quite different from experimental measurements. This paper proposes a new method to calculate the SNR of received UV signals, and then uses this value to select an optimal wavelet basis and analyzes the denoising performance.

The rest of this paper is organized as follows. Section II presents the model of NLOS UV multiple-scatter propagation and gives a detailed description on the denoising process for received UV signals using the wavelet transform. In order to better select suitable wavelet basis functions and effectively evaluate the denoising performance on UV signals, in Section III, a new SNR calculation method is presented. Using this method, the SNRs of both experimental signals and simulated signals are evaluated and compared. In Section IV, we use the SNR values calculated from the proposed method to guide the selection of an optimal wavelet basis function in wavelet transform denoising; then, we apply the wavelet denoising algorithm to the UV signals received at different transceiver elevation angles and different communication distances. Finally, we draw our conclusions in Section V.

II. SIGNAL DENOISING WITH WAVELET TRANSFORM

A. MULTI-SCATTERING TRANSMISSION MODEL BASED ON MONTE CARLO METHOD

A wireless UV multi-scattering transmission model is shown in Fig. 1, with the assumption that the origin of the coordinate system is at the position of the transmitter ($T_x$). The parameter $d$ is the distance between the transmitter and the receiver ($R_x$). $C_r$ and $C_l$ represent the $T_x$ beam cone and the $R_x$ field-of-view (FOV) cone, respectively. Signals are transmitted into the beam cone $C_r$. The elevation angle of $C_r$, denoted by $\theta_r$, is the angle between the central axis of $C_r$ and the projection of the central axis on the horizontal plane. The elevation angle of $C_l$, denoted by $\theta_l$, is calculated in a similar way to $\theta_r$. $\Phi_r$ and $\Phi_l$ denote the half-beam angle of $C_r$ and the half FOV angle of $C_l$, respectively. $r_1$ and $r_2$ are the off-axis angle of $C_l$ and $C_r$, respectively. $S_r$ is the first scattering point, $S_2$ is the next scattering point, and so on. $r_0$ is the distance from $T_x$ to $S_1$, $r_1$ is the distance from $S_1$ to $R_x$, $r_2$ is the distance from $S_2$ to $R_x$, and so on. The last scattering point is $S_n$ for the $n$-step scattering model.

As shown in Fig. 1, when a square wave signal passes through the multi-scattering transmission channel, a large amount of noise will be generated, which will cause the received UV waveform to be seriously deformed. In NLOS communications, the useful signal that reaches the $R_x$ through this scattering transmission is very weak and usually in a small signal state, and the noise becomes the main component of the received signal. To effectively reduce the noise, we need to develop suitable denoising methods.
component, so it is difficult to make sampling judgments after filtering. In addition, as the communication distance increases, the received signal level rapidly decays, and the range that the NLOS communication can reach becomes very limited. Therefore, in order to reduce the BER and improve the communication quality of UVC systems, it is necessary to perform noise reduction on received UV signals. In this paper, we adopt the wavelet transform (WT) denoising method which is presented as follows.

B. DENOISING METHODS USING DISCRETE WAVELET TRANSFORM

1) WAVELET DENOISING PROCESS

Assuming that a received UV signal \( f(n) \) is contaminated by noise \( e(n) \), a basic noise model can be expressed as:

\[
s(n) = f(n) + \sigma e(n)
\]

where \( e(n) \) is a Gaussian white noise, \( \sigma \) is the noise intensity, and \( n = 1, 2, 3, \ldots, N \) represents the length of the signal.

The overall process of the wavelet-based denoising scheme is shown in Fig. 2.

![FIGURE 1. Multi-scattering transmission model based on Monte Carlo method.](image)

![FIGURE 2. Process of wavelet transform denoising.](image)

As seen from Fig. 2, the denoising process involves the following three main steps.

(1) Wavelet Decomposition: select a wavelet and determine the number of levels to decompose the signal. As a result, the useful signal part is mainly concentrated in the approximate coefficients, and the noise part is mainly included in the detail coefficients.

(2) Wavelet Thresholding: select a threshold criterion and a threshold function to adjust the detail coefficients, and keep intact the approximate coefficients; and

(3) Wavelet Reconstruction: using the unchanged approximation coefficients and the modified detail coefficients, apply inverse discrete wavelet transform and achieve the data recovery.

2) DISCRETE WAVELET TRANSFORM

In this paper, discrete wavelet transform (DWT) is selected to denoise the noisy UV signals. The Wavelet Transform is a mathematical tool useful in the analysis of signals. It involves the decomposition of signals in terms of the following wavelet basis functions \( \psi(t) \) given by [35]:

\[
\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t - b}{a}\right)
\]

where \( a \) and \( b \) are the scaling and translation parameters, respectively. If the scaling and translation parameters are chosen as powers of two, the analysis will not lose accuracy, and become much more efficient. In this case, the discrete wavelet function can be written as [35]:

\[
\psi_{j,k}(n) = 2^{-j/2} \psi(2^{-j} n - k)
\]

The DWT can be described mathematically using a set of inner products between a finite-length sequence and a discretized wavelet basis. Each inner product results in a wavelet transform coefficient. Thus, the DWT of a finite-length sequence, \( s(n) \), can be expressed as:

\[
DWT(j, k) = \sum_{n=1}^{N} s(n) \cdot \psi_{j,k}^{*}(n)
\]

where \( DWT(j, k) \) is a DWT coefficient, and the superscript * denotes complex conjugate.

3) THRESHOLD SELECTION

A key challenge of thresholding is to determine a proper threshold value which reflects the estimated noise level of signal. If the threshold is too small, the wavelet coefficients after thresholding could still contain noise components. If the threshold is too large, the useful signal might be removed. This paper selects the Heursure threshold (denoted by \( \lambda_C \)) estimation rule to denoise the signal. It is a combination of $\text{Sqtwolog}$ methods and Rigrsure methods. We first define two variables, \( A \) and \( B \), as shown in Eq. (5) and Eq. (6),

\[
A = \frac{\sum_{n=1}^{N} w_n^2 - N}{N} \quad \text{(5)}
\]

\[
B = \sqrt{\frac{(\log_2 N)^3}{N}} \quad \text{(6)}
\]

where \( w_n \) represents a wavelet coefficient, and \( N \) is the length of wavelet coefficients.

The Heursure threshold selection principle is as follows: when \( A < B \), $\text{Sqtwolog}$ threshold (denoted by \( \lambda_A \)) is used; when \( A \geq B \), the smaller value between the $\text{Sqtwolog}$ threshold and the Rigrsure threshold (denoted by \( \lambda_B \)) is selected. In other words,

\[
\lambda_C = \begin{cases} 
\lambda_A & A < B \\
\min(\lambda_A, \lambda_B) & A \geq B
\end{cases}
\]

\[
\text{(7)}
\]
In the above principle, the Sqtwolog threshold selection rule is proposed by Donoho and Johnstone [36], and has been adopted in many practical applications. It is chosen to be,

$$\lambda_A = \sqrt{2\log N_j \cdot \text{median}(|w|)/0.6745}$$

(8)

where $N_j$ is the length of the noisy signal at the $j$th scale, and $w$ is a list of all the wavelet coefficients at scale $j$.

On the other hand, the Rigrsure threshold selection rule is obtained with the following procedure. First, we define a vector $W = [w_1, w_2, w_3, \ldots, w_N]$, consisting of all the wavelet coefficients of length $N$. The wavelet coefficients in $W$ are sorted in ascending order of their squared values, i.e., $w_1^2 \leq w_2^2 \leq \ldots \leq w_N^2$. Then we define a risk vector $R = [r_1, r_2, \ldots, r_N]$, where each element $r_n$, $n = 1, 2, \ldots, N$, is given as:

$$r_n = \frac{[N - 2n + (N - n) \times w_n + \sum_{i=1}^n w_i]}{N}$$

(9)

Next, select the smallest element $r_n$ from the vector $R$, then find the corresponding wavelet coefficient $w_n$ (with the same subscript) in the vector $W$. With that, the threshold by the Rigrsure threshold estimation rule is expressed as:

$$\lambda_R = \sigma \sqrt{w_n}$$

(10)

where $\sigma$ is the standard deviation of the noisy signal.

4) SOFT THRESHOLD FUNCTION

After the threshold value $\lambda$ is determined, we use a soft threshold function to modify the wavelet coefficients. The threshold function embodies the processing strategy of the wavelet coefficients that deviate from the threshold. The threshold function we choose is defined as follows: when the absolute value of a wavelet coefficient, denoted by $w_{j,k}$, is greater than the threshold $\lambda$, we replace this wavelet coefficient by subtracting the threshold $\lambda$ from the absolute value of $w_{j,k}$, and keeping the sign of $w_{j,k}$; otherwise, we set the wavelet coefficient to zero [37]. In other words, the new wavelet coefficients after thresholding are:

$$\eta(w_{j,k}) = \begin{cases} 
\text{sgn}(w_{j,k})(|w_{j,k}| - \lambda) & |w_{j,k}| \geq \lambda \\
0 & |w_{j,k}| < \lambda
\end{cases}$$

(11)

These modified wavelet coefficients, $\eta(w_{j,k})$, are then used in the wavelet reconstruction.

III. THE SINGAL-TO-NOISE RATIO CALCULATION METHOD

In order to evaluate the performance of the wavelet denoising method presented in Section II, here, we propose a new signal-to-noise ratio (SNR) calculation method to achieve better estimates on the SNR of UV signals. The SNR value—serving as a performance indicator—will guide us to select the best wavelet basis function. Traditionally, the SNR at the UV receiver is calculated by quantum limit methods; however, these methods have a major defect—the resulting SNR deviates far from the actual value obtained from experimental measurements. The proposed method differs from traditional techniques in that it calculates the SNR using the actual data received at the receiver.

This section will first present the procedures of this SNR calculation method for both experimental and simulated scenarios. Then, these procedures are implemented to evaluate the SNRs of the ultraviolet signals received at the receiver through experiments and simulations, and the results are discussed.

A. CALCULATING THE SNR OF EXPERIMENTAL SIGNALS

In our experiment, the transmitter uses a UV light emitting diode (LED) with a center wavelength of 265 nm. When the LED is lit, the current is measured as 150 mA and the optical power is 10 mW. A Hamamatsu photomultiplier tube (PMT) R7154 is used at the receiver end. The elevation angles of the transceiver are set as $\theta_t = \theta_r = 0^\circ$, and the cone half angles at the transceiver are set as $\Phi_t = 15^\circ$ and $\Phi_r = 40^\circ$. The distance between transmitter and receiver is 40 m. The transceiver sends a square wave signal with frequency of 1.1 kHz and 50% duty cycle. With these settings, the specific steps of calculating SNR are as follows.

Step 1: Take an ultraviolet signal collected at the receiver from the experiment, as displayed in Fig. 3 where 3633 sample points are selected. Noise is clearly visible at high and low levels of the received signal.

FIGURE 3. Calculating SNR of the received UV signal generated from experiments: (a) original experimental signal; (b) absolute value of experimental signal and its mean; (c) noise extracted from the received signal; and (d) noise power.

Step 2: Find the absolute value of the acquired UV signal, as shown in Fig. 3(b). Then, calculate the average value of the signal, which is shown by a red line in the figure. This value represents the useful signal; thus, the signal power is evaluated as the square of this average value divided by the load resistance.
Step 3: Subtract the average value from the received signal to obtain the noise part of the signal, as shown in Fig. 3(c).

Step 4: Calculate the noise power of the received signal using the noise part of Fig. 3(c): first square the noise, take the average, and then divide it by the load resistance to obtain the noise power.

Step 5: Calculate the SNR of the received UV signal with the formula in (12):

\[
    \text{SNR} = 10 \log_{10} \left( \frac{(\text{mean} |U|)^2}{\text{mean} |U - \text{mean} |U|^2} \right) \tag{12}
\]

where \(U\) is the voltage amplitude of the received UV signal and \(R = 100 \text{K}\Omega\) is the load resistance.

B. CALCULATING THE SNR OF SIMULATED SIGNALS

Now, we calculate the signal-to-noise ratio (SNR) of signals generated from the Monte Carlo (MC) simulations, by applying the same idea of the SNR calculation method for the experimental data. The multi-scattering model presented in Section II is used to simulate the UV communication system. Gaussian noises are formed from the multi-path transmission of the scattering channel. The impulse response obtained from the MC simulation matches with the experimental measurement very well.

The simulation is set up as follows: The transmitter sends a single pulse signal with energy of 1J; the starting time is 0 and the pulse width is 0.1ms; the geometric parameters of the transceiver are set as the same as those in the earlier experiments, i.e., \(\theta_t = \theta_r = 0^\circ\), \(\Phi_t = 15^\circ\) and \(\Phi_r = 40^\circ\); and the distance between transmitter and receiver is 40 m, the same as before.

\[
    \text{SNR} = 10 \log_{10} \left( \frac{(\text{mean} |P|)^2}{\text{mean} |P - \text{mean} |P|^2} \right) \tag{13}
\]

where \(P\) is the power density of the received UV signal and \(R = 100 \text{K}\Omega\).

C. IMPLEMENTING THE SNR CALCULATION METHOD

We apply the above SNR calculation procedures to the following two scenarios: (1) UV signals are transmitted and received with physical experiments; and (2) UV signals are generated with numerical simulations using the multi-scattering model. The results are compared and analyzed.

FIGURE 5. NLOS UV communication devices.

The outdoor testbed of UVC system we built for the experiments are shown in Fig. 5, where the emitter is an UV LED with a central wavelength of 265 nm and the receiver is a PMT R7154. The experiment was conducted in a sports field of Xi’an Polytechnic University in Shaanxi Province from 7 p.m. to 9 p.m. in March, 2019. The pulse signal generated at the transmitter has a loading frequency of 1.1 kHz and duty cycle of 50%. The transceiver elevation angles were set to 0°, 15°, and 30°, and the communication distance was varied from 20m to 100m with a step of 20m. Detailed experimental conditions and parameters are shown in Table 1.

For the computer simulation, we set the same physical configurations as used in the experiment. Additional parameters of the channel model are listed in Table 2. The transmitter sends a single pulse signal with energy of 1J and pulse width of 0.1ms, and the pulse starts at time 0. The rest of the parameters of the transceiver are shown in Table 3.
Signal-to-noise ratios are then calculated for both scenarios. Fig. 6 shows the SNR values of both the simulated and experimental signals received at the receiver under different elevation angles and communication distances. According to the results in Fig. 6, the two sets of curves share two common trends: (1) Under the same transceiver elevation angle, the SNR decreases as the communication distance increases; and (2) the larger the transceiver elevation angle, the lower the SNR. The SNR is weaken with higher transceiver elevation angle and longer communication distance. For instance, when the transceiver elevation angle is 30° and the communication distance is above 60 m, the SNR is below 5dB. These results verify that UV is more suitable for short distance communications.

Moreover, Fig. 6 shows that the SNR of the signals received from experiments mostly matches the one resulting from computer simulations. One exception is when the communication distance is 20m, where the SNR of the experimental signal is much higher. This could be the result of many factors (such as characteristics of experimental equipment and changes in the external environment) that affect the communication quality in the actual experiment, whereas the environment in the simulation is more ideal and steady.

IV. PERFORMANCE ANALYSIS OF NOISE REDUCTION BASED ON WAVELET TRANSFORM

In this section, the wavelet noise reduction algorithm described in Section II is performed on the signals obtained from both the experiments and the MC simulations. The SNRs before and after denoising are evaluated using the calculation method presented in Section III. We use the increase in SNR after denoising as a performance index of the denoising algorithm. With this index, we then study how changes in the transceiver elevation angles and communication distances affect the performance of the denoising algorithm.

A. WAVELET DENOISING RESULTS ON BOTH EXPERIMENTAL AND SIMULATED SIGNALS

Here we apply the wavelet denoising algorithm described in Section II to the UV signals received at the receiver. First, the signal is decomposed into four layers with the coif2 wavelet basis function. This basis function is selected to achieve a better denoising performance, and the selection process will be addressed in the next subsection. Then, we use the Heursure threshold criteria and the soft threshold processing function, addressed in Section II, to reshape the

![Figure 6. SNRs of the simulated signals and experimental signals under different transceiver distances.](image-url)
wavelet coefficients. In the end, the inverse wavelet transform is performed to reconstruct the signal.

The above operation is first applied to a UV signal received from the experiments, and the results are depicted in Fig. 7. The top subplot shows the raw UV signal received when the transceiver elevation angle is 0° and the communication distance is 40 m. The bottom subplot shows the signal after denoising. It can be seen that the burr is significantly reduced after denoising. The SNR values before and after denoising are shown in Table 4. It can be clearly seen that the SNR is improved by 8.0790 dB after denoising.

Next, the same operation is performed on a UV signal received after propagating through the multi-scattering channel simulation model. In the simulation, the transmitted signal is a single-pulse signal with energy of 1J, with a starting time of 0 and pulse width of 0.1 ms. The remaining parameters are the same as before. Fig. 8 illustrates the result. Again, it shows that the burr in the original signal is significantly reduced. The SNR values before and after denoising are listed in Table 5. We could see that the SNR value is greatly improved by 11.9803 dB after denoising.

### B. PERFORMANCE OF THE WAVELET DENOISING AT DIFFERENT TRANSCEIVER ELEVATION ANGLES

Now, we study the effect of transceiver elevation angles on the wavelet denoising performance. The signals we use here are generated from the simulation model instead of experiments, in that the simulation can offer steady channel conditions readily.

While the remaining geometric parameters are fixed at α_t = α_r = 0°, and Φ_t = 15°, Φ_r = 40°, d = 40m, the transceiver elevation angle is varied from 0° to 80° with step of 10°. The other parameters are the same as in Table 2.

First, we would like to select a wavelet basis which offers better performance than others for the wavelet denoising algorithm presented in Section II. To this end, we use each of the four common wavelet bases—fk wavelet basis, sym wavelet basis, db wavelet basis, and coif wavelet basis—to denoise the same UV signal. The SNRs of the resulting signals after denoising are evaluated with our calculation method for each case and compared in Fig. 9.

Each curve in Fig 9(a), corresponding to each wavelet basis, records the SNRs of the denoised signals when the original signals are generated at different transceiver elevation angles. It is shown that as the transceiver elevation angle increases, all four curves show a downward trend. Even though the performance of all four types of wavelets are similar, the SNRs of the denoised signals with the coif wavelet basis is consistently higher than others, and can reach 37.0870dB at low transceiver elevation angles.

Thus, we further try different orders of the wavelet coif family, i.e., coif1, coif2, coif3, coif4, and coif5 basis functions, to process the noisy signal, for which the results are shown in Fig. 9(b). All five curves in Fig. 9(b) almost overlap. If zooming in closely, we can see that the coif2 wavelet basis slightly outperforms the others. Therefore, the coif2 wavelet basis is our best choice for the wavelet denoising algorithm.

Next, we evaluate the SNRs before and after denoising using the coif2 wavelet basis for the signals received at
smaller the transceiver elevation angle, the better the quality of wireless ultraviolet communication. The top curve in Fig. 10 draws the SNRs of the signals after denoising using the coif2 wavelet basis. Comparing the two curves, we see that the wavelet transform denoising algorithm can effectively remove the noise component from the received UV signal, and that the improved SNR can reach a maximum of 11.9941dB.

**C. PERFORMANCE OF THE WAVELET DENOISING FOR DIFFERENT COMMUNICATION DISTANCES**

Applying the same analysis procedure used above, we examine the effect of the communication distance on the performance of our wavelet denoising algorithm. Except the transceiver distance, all the remaining geometric parameters are fixed at $\alpha_t = \alpha_r = 0^\circ$, $\Phi_t = 15^\circ$, $\Phi_r = 40^\circ$, and $\theta_r = \theta_t = 10^\circ$. The other parameters are the same as in Table 2.

Fig. 11(a) shows the SNR values after wavelet denoising for the signals obtained at different communication distances. Each curve corresponds to one of the four wavelet bases, and (b) different coif wavelet bases.

Fig. 11(a) shows the SNR values after wavelet denoising for the signals obtained at different communication distance. Each curve corresponds to one of the four wavelet bases,
which are the $\textit{fk}$ wavelet basis, $\textit{syn}$ wavelet basis, $\textit{db}$ wavelet basis, and $\textit{coif}$ wavelet basis. As the communication distance increases, all four curves show a downward trend, which confirms that UV is more suitable for short distance communication. In addition, agreeing with the earlier case where the transceiver elevation angle varies, using the $\textit{coif}$ wavelet basis results in the highest SNR values consistently for all communication distances.

Then, we use different orders of the wavelet bases in the $\textit{coif}$ family—the $\textit{coif}1$, $\textit{coif}2$, $\textit{coif}3$, $\textit{coif}4$, and $\textit{coif}5$ wavelet bases to reprocess the noisy signal. As before, the communication distance is varied from 10m to 100m with step of 10m. The result, as shown in Fig. 11(b), suggests that the $\textit{coif}2$ is superior to the others; therefore, we select the $\textit{coif}2$ wavelet for the subsequent analysis.

Next, using the $\textit{coif}2$ wavelet, we apply the same wavelet denoising algorithm to the UV signals received with different communication distances. SNRs are evaluated for both the original signals as well as the denoised signals. The results are depicted in Fig. 12.

![Comparison of SNRs before and after denoising of the UV signals received at different distances](image)

**FIGURE 12.** Comparison of SNRs before and after denoising of the UV signals received at different communication distances.

We can see that as the communication distance increases, the system SNR declines significantly. The SNR value after denoising has improved by 11.9857 dB on average for different communication distances. Once again, the above results show that the wavelet transform denoising method can effectively remove the noise component of the UV signals and improve their SNRs.

**V. CONCLUSION**

This paper applies a wavelet denoising algorithm to process the ultraviolet (UV) signals which are received at the receiver of a wireless UV communication system. The algorithm is implemented to the signals generated through experiments as well as with simulations. The performance of this wavelet-based algorithm is measured by the improved signal-to-noise ratio (SNR) after denoising. In order to evaluate SNRs more accurately, this paper proposes a new method to numerically calculate the SNRs of the received UV signals, which is proven to be very effective.

With the help of the proposed SNR calculation method, we carefully identify the best wavelet basis function so that it results in the highest SNR among all candidate basis functions. With the selected wavelet basis, the wavelet denoising process is applied to both the UV signals generated from the multi-scattering transmission simulation model and the signals received from physical experiments. For both the simulations and experiments, the signals are generated with various settings on communication distances and transceiver elevation angles. The results are analyzed and compared.

We conclude that the proposed SNR calculation method is feasible and can accurately evaluate the SNR of received UV signals. In addition, the calculated SNR value can guide the selection of the most effective wavelet basis function. The results also show that the performance of the selected denoising method (the wavelet basis is $\textit{coif}2$) on UV signals is highly satisfactory—the SNR is increased by 11.9925 dB on average after denoising.

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