Predicting the settlement of Urumqi subway based on wavelet denoising and BP neural network

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Abstract. In this study, we propose a model to accurately predict the ground subsidence caused by subway excavation using the wavelet denoising model and BP neural network. First, we develop an optimal denoising model by comparing and analyzing the denoising effect of different wavelet denoising parameters. The model is used to reduce the noise of the monitoring data. Then, we utilize BP neural network to develop a prediction model in which the proposed denoising model is used. Finally, we apply the proposed model to Urumqi subway. The results demonstrate the rationality and accuracy of the proposed model.

Key word. Wavelet denoising; BP neural network; Settlement prediction

1. Introduction
With the growth of the city population and the expansion of urban scale, underground engineering is rapidly developing in China. However, the construction of underground engineering inevitably causes surface deformation. When the surface deformation exceeds the safety limit, it will affect the safe operation of underground work and the regular use of surrounding buildings and will cause serious casualties. Therefore, accurate prediction of surface deformation caused by underground construction is crucial for disaster prevention and mitigation [1-5].

Currently, the empirical method [6-8], numerical simulation [9-10], analysis [11], and artificial neural network [12-16] are commonly used to predict the surface deformation induced by the construction of underground engineering. Among them, artificial neural network is widely used because of advantages such as simplicity, small computational cost, and strong parallelism. Moreover, monitoring data inevitably contain noise pollution due to the influence of measuring instruments, human operation, observation conditions, and other factors. Wavelet transform has an excellent performance in signal denoising [17-19].

To eliminate noise and improve the prediction accuracy, several studies have used the prediction model of the wavelet denoising combined with neural network. Zheng Y Y used the wavelet transform principle to reduce the monitoring noise, and used neural network to analyze the prediction effect and accuracy for different training samples [20]. Jialong S predicted the deformation caused by grouting around mine shaft by combining wavelet analysis and neural network [21]. In this study, based on the monitoring data of Urumqi Rail Transit Line 1, the wavelet theory was used to reduce the noise of the monitoring data and predict the ground subsidence using the BP neural network. Our model provides a reference for the subsidence prediction of Urumqi metro.
2. Project overview

Based on the monitoring data of the Beimen Station of Urumqi Rail Transit Line No. 01 as an example, the configuration is shown in figure 1. Sixteen monitoring points are set around the station to reflect surface deformation. Among them, the monitoring point DB-02-01 is arranged around the station and along the metro lines. It bears double destabilization that can be attributed to excavation tunnel and foundation pit and is more representative than the remaining points. In this study, we select the accumulated settlement of DB-02-01 monitoring point for research purposes. The original data are plotted in figure 2. Due to the error of the original data, the settlement curve locally fluctuates, which is inconsistent with the actual deformation trend. Therefore, it is necessary to reduce the noise of the original data before settlement prediction.

3. Data denoising

Recently, wavelet analysis is a rapidly developing signal processing technology. It is known as a "mathematical microscope" because it can perform time-frequency analysis for multilayer resolutions [22-23]. Due to the different time-frequency characteristics of real signal and noise in monitoring data, wavelet denoising can effectively separate them to reduce the error and obtain real deformation information [24]. Generally, the steps of wavelet denoising are as follows [25-30]: a) choose the appropriate wavelet function, level and decomposition order to decompose the monitoring signal according to the actual characteristics of the project; b) process the threshold value; c) reconstruct the signal by wavelet transform. There are two main methods to evaluate the effect of wavelet denoising: (1) the root mean square error (RMSE), which refers to the mean square error between the denoised signal and the original signal. The smaller the RMSE is, the better the denoising effect is. (2) Signal to noise ratio
(SNR), which refers to the energy ratio of the original signal and noise. The higher the SNR is, the better the denoising performance is. Before applying wavelet transformation to denoise the original data, the influence of various parameters on the denoising effect is considered to obtain the optimal denoising model and achieve the optimal denoising effect.

3.1. Influence of different thresholds on the denoising effect

Based on related studies in literature, the wavelet functions dbN and symN that are widely used in engineering to decompose the monitoring signal into three layers are used. To select the appropriate threshold, the denoising effects of different thresholds are compared (table 1 and figure 3).

**Table 1.** The denoising effects of different thresholds.

| dbN  | Soft threshold | Hard threshold | symN      | Soft threshold | Hard threshold |
|------|----------------|----------------|-----------|----------------|----------------|
|      | SNR  | RMSE | SNR  | RMSE | SNR  | RMSE | SNR  | RMSE |
| db1  | 20.57 | 0.17 | 22.27 | 0.14 | sym1 | 20.58 | 0.17 | 22.27 | 0.14 |
| db2  | 21.30 | 0.15 | 25.68 | 0.09 | sym2 | 21.30 | 0.15 | 25.68 | 0.09 |
| db3  | 20.27 | 0.17 | 23.95 | 0.11 | sym3 | 20.27 | 0.17 | 23.95 | 0.11 |
| db4  | 20.39 | 0.17 | 23.63 | 0.12 | sym4 | 21.36 | 0.15 | 24.04 | 0.11 |
| db5  | 21.03 | 0.16 | 22.78 | 0.13 | sym5 | 20.20 | 0.18 | 22.73 | 0.13 |
| db6  | 18.26 | 0.22 | 19.39 | 0.19 | sym6 | 20.83 | 0.16 | 23.57 | 0.12 |
| db7  | 25.02 | 0.10 | 30.18 | 0.06 | sym7 | 20.11 | 0.18 | 22.95 | 0.13 |
| db8  | 22.64 | 0.13 | 28.62 | 0.07 | sym8 | 21.03 | 0.16 | 23.29 | 0.12 |
| db9  | 22.07 | 0.14 | 25.90 | 0.09 | sym9 | 20.54 | 0.17 | 22.92 | 0.13 |
| db10 | 24.58 | 0.11 | 30.23 | 0.06 | sym10 | 19.55 | 0.19 | 22.10 | 0.14 |

**Figure 3.** The denoising effects of different thresholds.

Figure 3 shows that the RMSE of different thresholds are similar regardless of the wavelet function. However, the SNR of hard threshold is significantly higher than that of the soft threshold. Thus, it can be concluded that the denoising effect of hard threshold is better than that of the soft one.

3.2. Influence of different threshold selection rules on the denoising effect

In the process of wavelet denoising, there are four kinds of threshold selection rules: sqtwolog, minimaxi, rigrsure, and heursure thresholds. The dbN and symN wavelet functions are also used to decompose the monitoring signal into three layers, and the above four thresholds are applied to denoise the monitoring data, respectively. The denoising results are shown in table 2 and figure 4 as follows:
Table 2. Comparison of denoising effect using four thresholds.

| dbN   | sqtwolog | minimaxi | rigrsure | heursure |
|-------|----------|----------|----------|----------|
| SNR   | RMSE     | SNR      | RMSE     | SNR      | RMSE     | SNR     | RMSE     |
| db1   | 19.49    | 0.19     | 22.15    | 0.14     | 22.27    | 0.14    | 20.97    | 0.16     |
| db2   | 15.91    | 0.29     | 20.15    | 0.18     | 25.68    | 0.09    | 17.75    | 0.23     |
| db3   | 16.97    | 0.26     | 21.80    | 0.15     | 23.95    | 0.11    | 20.17    | 0.18     |
| db4   | 16.96    | 0.26     | 21.98    | 0.14     | 23.63    | 0.12    | 18.37    | 0.22     |
| db5   | 17.25    | 0.25     | 20.76    | 0.16     | 22.78    | 0.13    | 17.73    | 0.23     |
| db6   | 17.26    | 0.25     | 19.68    | 0.19     | 19.39    | 0.19    | 19.22    | 0.20     |
| db7   | 18.02    | 0.23     | 22.33    | 0.14     | 30.18    | 0.06    | 19.46    | 0.19     |
| db8   | 17.48    | 0.24     | 21.11    | 0.16     | 28.62    | 0.07    | 18.77    | 0.21     |
| db9   | 17.12    | 0.25     | 22.10    | 0.14     | 25.90    | 0.09    | 18.15    | 0.22     |
| db10  | 18.59    | 0.21     | 23.13    | 0.16     | 30.23    | 0.06    | 20.70    | 0.17     |

| symN  | sqtwolog | minimaxi | rigrsure | heursure |
|-------|----------|----------|----------|----------|
| SNR   | RMSE     | SNR      | RMSE     | SNR      | RMSE     | SNR     | RMSE     |
| sym1  | 19.49    | 0.19     | 22.15    | 0.14     | 22.27    | 0.14    | 20.97    | 0.16     |
| sym2  | 15.91    | 0.29     | 20.15    | 0.18     | 25.68    | 0.09    | 17.75    | 0.23     |
| sym3  | 16.97    | 0.26     | 21.80    | 0.15     | 23.95    | 0.11    | 20.17    | 0.18     |
| sym4  | 18.32    | 0.22     | 21.55    | 0.15     | 24.04    | 0.11    | 19.23    | 0.20     |
| sym5  | 17.16    | 0.25     | 21.21    | 0.16     | 22.73    | 0.13    | 17.99    | 0.23     |
| sym6  | 17.27    | 0.25     | 19.95    | 0.18     | 23.57    | 0.12    | 18.59    | 0.21     |
| sym7  | 16.74    | 0.26     | 20.90    | 0.16     | 22.95    | 0.13    | 18.67    | 0.21     |
| sym8  | 17.30    | 0.25     | 20.20    | 0.18     | 23.29    | 0.12    | 19.59    | 0.19     |
| sym9  | 17.27    | 0.25     | 21.71    | 0.15     | 22.92    | 0.13    | 19.14    | 0.20     |
| sym10 | 16.93    | 0.26     | 20.11    | 0.18     | 22.10    | 0.14    | 18.57    | 0.21     |

Figure 4. Comparison of denoising effect using four threshold rules.

Figure 4 shows that regardless of the wavelet function used, the RMSE generated by denoising with different threshold selection rules is similar. However, the SNR of rigrsure threshold is the highest, indicating that the denoising effect of rigrsure threshold is the best, followed by the minimaxi threshold, then the heursure threshold, and finally the sqtwolog threshold.
3.3. About scal
Scal defines multiplicative threshold rescaling, and scal = one for no rescaling; scal = sln for rescaling using a single estimation of level noise based on first-level coefficients; scal = mln for rescaling using level-dependent estimation of level noise. The above three methods are used, respectively, to filter the noise; the results are shown in Table 3 and Figure 5:

Table 3. Comparison of denoising effect using different scal.

| dbN  | one |       |       |       |       |       |
|------|-----|-------|-------|-------|-------|-------|
|      | SNR | RMSE  | SNR   | RMSE  | SNR   | RMSE  |
| db1  | 14.53 | 0.34  | 22.27 | 0.14  | 21.46 | 0.15  |
| db2  | 13.57 | 0.38  | 25.68 | 0.09  | 21.44 | 0.15  |
| db3  | 14.42 | 0.34  | 23.95 | 0.11  | 20.04 | 0.18  |
| db4  | 14.38 | 0.34  | 23.63 | 0.12  | 18.92 | 0.20  |
| db5  | 13.65 | 0.37  | 22.78 | 0.13  | 20.38 | 0.17  |
| db6  | 11.58 | 0.47  | 19.39 | 0.19  | 18.08 | 0.22  |
| db7  | 14.09 | 0.36  | 30.18 | 0.06  | 22.76 | 0.13  |
| db8  | 12.35 | 0.43  | 28.62 | 0.07  | 21.70 | 0.15  |
| db9  | 13.25 | 0.39  | 25.90 | 0.09  | 22.09 | 0.14  |
| db10 | 11.52 | 0.48  | 30.23 | 0.06  | 23.08 | 0.13  |

| symN | one |       |       |       |       |       |
|------|-----|-------|-------|-------|-------|-------|
|      | SNR | RMSE  | SNR   | RMSE  | SNR   | RMSE  |
| sym1 | 14.53 | 0.34  | 22.27 | 0.14  | 21.46 | 0.15  |
| sym2 | 13.57 | 0.38  | 25.68 | 0.09  | 21.44 | 0.15  |
| sym3 | 14.42 | 0.34  | 23.95 | 0.11  | 20.04 | 0.18  |
| sym4 | 13.37 | 0.39  | 24.04 | 0.11  | 23.40 | 0.12  |
| sym5 | 13.66 | 0.37  | 22.73 | 0.13  | 23.01 | 0.13  |
| sym6 | 14.00 | 0.36  | 23.57 | 0.12  | 21.44 | 0.15  |
| sym7 | 13.99 | 0.36  | 22.95 | 0.13  | 22.95 | 0.13  |
| sym8 | 13.92 | 0.36  | 23.29 | 0.12  | 22.18 | 0.14  |
| sym9 | 14.02 | 0.36  | 22.92 | 0.13  | 22.59 | 0.13  |
| sym10| 14.47 | 0.34  | 22.10 | 0.14  | 20.25 | 0.17  |

(a) dbN wavelet function  (b) symN wavelet function

Figure 5. Comparison of denoising effect using different scal.
Figure 5 shows that regardless of the wavelet function used, the SNR of \textit{scal} = \textit{sln} is significantly higher than the others, indicating that the denoising effect of the case with \textit{scal} = \textit{sln} is better than the case with \textit{scal} = \textit{mln} and \textit{scal} = \textit{one}.

3.4. \textit{Influence of different wavelet functions on the denoising effect}

To obtain the appropriate wavelet function, the denoising effects of wavelet functions \textit{dbN} and \textit{symN} are compared, the results are shown in table 4.  

| \textbf{Table 4. Comparison of denoising effect using different wavelet functions.} |
|-----------------|----------------|----------------|----------------|----------------|----------------|
| \textbf{dbN}   | \textbf{SNR}  | \textbf{RMSE} | \textbf{symN}  | \textbf{SNR}  | \textbf{RMSE}  |
| db1            | 22.27         | 0.14          | sym1          | 22.27         | 0.14          |
| db2            | 25.68         | 0.09          | sym2          | 25.68         | 0.09          |
| db3            | 23.95         | 0.11          | sym3          | 23.95         | 0.11          |
| db4            | 23.63         | 0.12          | sym4          | 24.04         | 0.11          |
| db5            | 22.78         | 0.13          | sym5          | 22.73         | 0.13          |
| db6            | 19.39         | 0.19          | sym6          | 23.57         | 0.12          |
| db7            | 30.18         | 0.06          | sym7          | 22.95         | 0.13          |
| db8            | 28.62         | 0.07          | sym8          | 23.29         | 0.12          |
| db9            | 25.90         | 0.09          | sym9          | 22.92         | 0.13          |
| db10           | 30.23         | 0.06          | sym10         | 22.10         | 0.14          |
| average        | 25.26         | 0.11          | average       | 23.35         | 0.12          |
| variance       | 3.39          | 0.04          | variance      | 0.99          | 0.01          |

Table 4 reveals that the SNR corresponding to \textit{dbN} wavelet function is greater than \textit{symN} wavelet function, and the RMSE of \textit{dbN} wavelet function is less than \textit{symN} wavelet function, showing that the denoising effect of \textit{dbN} wavelet function is better than that of \textit{symN} wavelet function.

3.5. \textit{Influence of different decomposition levels on the denoising effect}

The \textit{dbN} wavelet function, hard threshold, \textit{rigrsure}, and \textit{scal} = \textit{sln} are used to denoise the original data with different decomposition levels, the denoising results are shown in table 5:

| \textbf{Table 5. Comparison of denoising effect using different levels.} |
|-----------------|----------------|----------------|----------------|----------------|----------------|
| \textbf{dbN}   | \textbf{lev} 1 | \textbf{lev} 2 | \textbf{lev} 3 | \textbf{lev} 4 | \textbf{lev} 5 | \textbf{lev} 6 | \textbf{lev} 7 | \textbf{lev} 8 |
| \textbf{SNR}  | \textbf{RMSE} | \textbf{SNR}  | \textbf{RMSE} | \textbf{SNR}  | \textbf{RMSE} | \textbf{SNR}  | \textbf{RMSE} | \textbf{SNR}  |
| db1   | 24.06 | 0.11 | 22.28 | 0.14 | 22.27 | 0.14 | 22.27 | 0.14 | 22.27 | 0.14 |
| db2   | 26.12 | 0.09 | 25.82 | 0.09 | 25.68 | 0.09 | 25.28 | 0.10 | 25.28 | 0.10 |
| db3   | 25.92 | 0.09 | 24.49 | 0.11 | 23.95 | 0.11 | 23.93 | 0.11 | 23.93 | 0.11 |
| db4   | 24.94 | 0.10 | 23.63 | 0.12 | 23.63 | 0.12 | 23.55 | 0.12 | 23.55 | 0.12 |
| db5   | 22.87 | 0.13 | 22.87 | 0.13 | 22.78 | 0.13 | 22.77 | 0.13 | 22.77 | 0.13 |
| db6   | 21.23 | 0.16 | 19.40 | 0.19 | 19.39 | 0.19 | 19.39 | 0.19 | 19.39 | 0.19 |
| db7   | 31.49 | 0.05 | 30.40 | 0.05 | 30.18 | 0.06 | 30.02 | 0.06 | 30.02 | 0.06 |
| db8   | 29.79 | 0.06 | 28.63 | 0.07 | 28.62 | 0.07 | 28.62 | 0.07 | 28.62 | 0.07 |
| db9   | 26.76 | 0.08 | 25.87 | 0.09 | 25.90 | 0.09 | 25.89 | 0.09 | 25.89 | 0.09 |
| db10  | 32.52 | 0.04 | 30.22 | 0.06 | 30.23 | 0.06 | 30.19 | 0.06 | 30.19 | 0.06 |
| average | 26.57 | 0.09 | 25.36 | 0.11 | 25.26 | 0.11 | 25.19 | 0.11 | 25.19 | 0.11 |
| variance | 3.49 | 0.03 | 3.39 | 0.04 | 3.39 | 0.04 | 3.36 | 0.01 | 3.36 | 0.01 |
From Table 5, in the process of dbN wavelet denoising, as the decomposition layers increase, the SNR decrease, while the RMSE's increase. When Lev = 1, the SNR is the largest and the RMSE is the smallest. Thus, we choose Lev = 1.

### 3.6. Influence of different wavelet orders on the denoising effect

To determine the wavelet order, the average and variance of dbN wavelet function under different decomposition levels (Lev = 1–12) are calculated, and the results are shown in the following figure:

![Figure 6. Influence of different wavelet orders on denoised effect.](image)

Figure 6 shows that the SNR of the db3 wavelet function is the highest, indicating that the denoising effect of db3 is the best. Therefore, db3 is selected to filter the noise.

To sum up, the db3 wavelet function is used to analyze the original monitoring data of DB-02-01 based on hard threshold, rigrsure, scal = sln and Lev = 1. The denoised data are shown in Table 6, while the comparison with the original data is shown in Figure 7.
Table 6. The denoised data of DB-02-01.

| periods | time /d | settlement /mm | periods | time /d | settlement /mm | periods | time /d | settlement /mm |
|---------|---------|----------------|---------|---------|----------------|---------|---------|----------------|
| 1       | 1       | 5.7755         | 20      | 30      | -0.1698        | 38      | 60      | 1.3291        |
| 2       | 3       | 4.1765         | 21      | 31      | -0.0814        | 39      | 64      | 1.2786        |
| 3       | 6       | 4.1565         | 22      | 32      | 0.0074         | 40      | 67      | 1.1116        |
| 4       | 8       | 3.9096         | 23      | 33      | 0.0433         | 41      | 71      | 0.7276        |
| 5       | 9       | 4.0100         | 24      | 34      | 0.0516         | 42      | 74      | 1.0020        |
| 6       | 10      | 2.7900         | 25      | 36      | 0.7576         | 43      | 78      | 0.8524        |
| 7       | 12      | 0.7891         | 26      | 37      | 0.1210         | 44      | 81      | 0.8079        |
| 8       | 13      | 0.9278         | 27      | 39      | 0.3867         | 45      | 85      | 0.8358        |
| 9       | 15      | -0.2989        | 28      | 41      | 0.4810         | 46      | 89      | 0.8990        |
| 10      | 17      | -0.0739        | 29      | 43      | 0.5683         | 47      | 92      | 0.9130        |
| 11      | 18      | -0.3897        | 30      | 44      | 0.6678         | 48      | 96      | 0.9302        |
| 12      | 19      | -0.4000        | 31      | 46      | 0.6449         | 49      | 100     | 0.6801        |
| 13      | 20      | -0.4821        | 32      | 48      | 0.5750         | 50      | 103     | 0.3127        |
| 14      | 22      | -0.5089        | 33      | 50      | 0.5789         | 51      | 107     | 0.2422        |
| 15      | 23      | -0.5137        | 34      | 52      | 0.5793         | 52      | 111     | 0.2148        |
| 16      | 24      | -0.4909        | 35      | 55      | 0.5578         | 53      | 116     | 0.2335        |
| 17      | 25      | -0.4609        | 36      | 57      | 0.5330         | 54      | 120     | 0.3234        |
| 18      | 26      | -0.4125        | 37      | 59      | 0.8584         | 55      | 124     | 0.4234        |
| 19      | 28      | -0.3078        |         |         |                |         |         |                |

Figure 7. Comparison between the original data and denoised data.

Figure 7 shows that in the three-time periods of 40–60 days, 75–90 days, and 105–120 days, the monitoring data contain significant contamination, which is also why the monitoring curve appears “spikes.” After the wavelet denoising, the monitoring curve becomes flat and closer to the real deformation.

4. Settlement prediction and analysis

We establish the structure of 31-18-1 BP neural network. That is, we construct a function fitting neural network with the size of the input as 31, the hidden is 18, and the output is 1. The monitoring data of the 1st to 45th periods are used as the learning set of the neural network, and the BP neural network algorithm is implemented by MATLAB. The monitoring data of the 46th to 55th periods are used as the test set to verify the accuracy of the prediction model. The comparison between the predicted data of BP neural network and denoised data is shown in table 7.
Table 7. Comparison between the predicted data of BP neural network and denoised data.

| periods | original data | predicted data | absolute error | relative error |
|---------|---------------|----------------|----------------|----------------|
|         |               |                |                |                |
| 46      | 0.7766        | 0.0534         | 6.43%          | 0.0534         |
| 47      | 0.5660        | 0.0440         | 7.21%          | 0.0440         |
| 48      | 0.4435        | 0.0335         | 8.17%          | 0.0335         |
| 49      | 0.6652        | 0.0648         | 8.88%          | 0.0648         |
| 50      | 0.3986        | 0.0414         | 9.41%          | 0.0414         |

| de-noised data | predicted data | absolute error | relative error |
|----------------|----------------|----------------|----------------|
|                | 0.9176         | 0.0186         | 2.07%          |
|                | 0.9295         | 0.0165         | 1.81%          |
|                | 0.9470         | 0.0168         | 1.81%          |
|                | 0.7004         | 0.0203         | 2.98%          |
|                | 0.3107         | 0.0020         | 0.61%          |

|         |    |      |      |      |      |
|---------|----------------|----------------|----------------|
|         | 51  | 52   | 53   | 54   | 55   |
| original data | predicted data | absolute error | relative error |
|               | 0.4432 | 1.0774 | 1.1095 | 1.2937 | 1.1491 |
|               | 0.0368 | 0.0574 | 0.0905 | 0.0863 | 0.0691 |
|               | 7.67%  | 5.63%  | 7.54%  | 6.25%  | 6.40%  |

| denoised data | predicted data | absolute error | relative error |
|---------------|----------------|----------------|----------------|
|               | 0.2322         | 0.01           | 4.13%          |
|               | 0.2145         | 0.0003         | 1.4%           |
|               | 0.2293         | 0.0042         | 1.8%           |
|               | 0.3342         | 0.0108         | 3.34%          |
|               | 0.4300         | 0.0066         | 1.56%          |

Table 7 shows that the relative error between the predicted value and the true value is kept within 10%, and the relative error is within 5% after the wavelet denoising. This shows that our model is reasonable. Meanwhile, the methods are simple and easy to use in practice, and one may incorporate these methods to accurately predict deformation.

5. Conclusion
In this study, a combination of wavelet denoising and BP neural network is used to develop a model for predicting subway construction settlement. The model fully reflects the prediction performance of BP neural network.

According to the noise reduction of the monitoring data, the method of the hard threshold is better than the soft threshold, and the denoising effect of the dbN wavelet function is better than the symN wavelet function. This provides a reference for ground settlement data processing caused by similar subway construction in the future.

By using BP neural network to predict the settlement of the denoised data, the results showed that the prediction error of the data after noise reduction is less than 5%, and the highest accuracy can reach 99.86%, validating the reliability and accuracy of the prediction model used in this study.

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