Agricultural Monitoring Based on Internet of Things and Remote Sensing

Xiaoyu Xu
College of Physics and Electronic Engineering, Mudanjiang Normal University, Mudanjiang 157000, Heilongjiang, China

Abstract

The parameters of agricultural ecological environment with fast time-varying characteristics are monitored based on Internet of Things and remote sensing, and the intensive spatial and time-continuous information of agricultural ecological environment (such as temperature, humidity, soil moisture, etc.) is obtained. The remote sensing image monitoring of agricultural ecological environment information is realized by using the wavelet analysis method. This paper proposes an adaptive threshold de-noising method which integrates the neighborhood information after image transformation. It establishes the adaptive threshold function to overcome the defects of soft and hard threshold functions, provides the thresholds of different scales and different directions according to the characteristics of wavelet transform, conducts adaptive threshold processing on the image and remove as many noises as possible by increasing thresholds on the high-frequency coefficients of the image. Then, it conducts mean filtering again on the high-frequency coefficients of the first-layer restricted image. Finally, it performs inverse wavelet transform. The simulation experiment proves that with this method, we can obtain a higher PSNR and that the algorithm of this paper can better preserve the edge details of the image and have a better de-noising effect compared with other conventional de-noising methods. This paper lays a foundation for timely and accurate acquisition of multi-dimensional information, effective fusion of multi-source information and intelligent dynamic diagnosis and analysis of large-scale, cross-regional, multi-point and multi-scale agricultural monitoring. It has innovative significance and practical application value.

Key words: Agricultural Monitoring, Internet of Things, Remote Sensing Images, Wavelet Analysis

1. Introduction

With the in-depth application of new information technologies such as Internet of Things, remote sensing and wavelet analysis in the development of modern agriculture, the future agricultural monitoring work is bound to develop towards automation and intellectualization, automatic data collection, automatic data analysis, real-time upload of monitoring and early warning information, and the development of intelligent agricultural monitoring and early warning. Service system will become the main feature of agricultural remote sensing monitoring and early warning in the future. Due to the influence of weather, remote-sensing devices and transmission medium, remote sensing image is always affected by many noises in the imaging and transmission. Among them, the most frequent noises include Gaussian noise, cloud noise and fog noise. These noises will directly affect further processing, analysis and application of the remote sensing image and decrease the value in use of the data. If such type of problems can be better resolved, it can better promote the development of image processing and the further classification and utilization of remote sensing image [1] [2]. The energy of noises in the remote sensing image also belongs to the high-frequency part, making noises cross with the detail signals of the remote sensing image. Nevertheless, the traditional de-noising method based on Fourier transform encounters contradiction between the elimination of noises and the preservation of edges because Fourier transform de-noising method is a global transformation. It is either in the space domain or the frequency domain completely [3].

In the 1960s and 1970s, linear processing methods are used in the field of digital image processing and the most typical is Fourier analysis. It can analyze the signals with time domain and frequency domain, laying a solid mathematical foundation for analyzing the signals with time-frequency domain [4] [5]. Get rid of the noises in the digital image with wavelet transform and proceed with the image reconstruction. It can not only preserve the edge detail information of the image, but it is also very adaptive, fast in calculation and little dependent on the prior knowledge of the signal because wavelet transform has the characteristics of decorrelation, low entropy, multi-resolution and flexible basis selection [6]. In the 1990s, Donoho and Johnstone from Stanford University had proposed the wavelet threshold de-noising method, constructed the universal threshold and justified its optimality. But the universal threshold is set according to the number of wavelet coefficients and it seems to obliterate wavelet coefficients; therefore, after de-noising, too much detail
information will be lost and the image becomes too smooth. We can select the proper de-noising method according to the features of remote sensing image and the size of noise variance so as to take a targeted step to remove the noises in the image more effectively [7, 8]. With the development of Internet of things technology, especially the development of low-cost and high-precision sensor production technology, the application of Internet of things technology in agriculture will continue to expand, especially the integration of remote sensing technology and wavelet analysis will effectively promote the development of digital agriculture.

This paper, first and foremost, analyzes several remote sensing de-noising methods, including median filtering and the classical wavelet threshold de-noising. The following work has been completed in this part: analyze and studied the decomposition of conventional wavelet, selection of wavelet and the impact of image de-noising. Under different noises, it also analyzes the strengths and weaknesses of different de-noising methods. Through analysis and comparison, it comes up with the improved algorithm based on adaptive wavelet threshold, conducts experiment of remote sensing image and obtains the value of peak signal to noise ratio and mean square error. It can be found through comparison that the algorithm of this paper can obtain a higher peak signal to noise ratio and better de-noising effect.

2. Adaptive Analysis of Wavelet Window Function

See wavelet \( \psi(t) \) as a window function and understand the time-frequency localization ability of wavelet transform with time-frequency window. Here, \( [\cdot] \) represents modulo operation and \( ||\cdot|| \) is the number of norms in the space. In \( L^2(\mathbb{R}) \), the norm is

\[
||f|| = \langle f, f \rangle = \left[ \int_{\mathbb{R}} |f(x)|^2 \, dx \right]^{1/2} \quad (1)
\]

Assume that the mother wavelet \( \psi(t) \) has finite support, namely the region with concentrated energy of wavelet function, then

\[
t^* = \frac{1}{||\psi||} \int_{\mathbb{R}} t |\psi(t)|^2 \, dt \quad (2)
\]

is the time window center and

\[
\Delta t = \frac{1}{||\psi||} \left[ \int_{\mathbb{R}} (t-t^*)^2 |\psi(t)|^2 \, dt \right]^{1/2} \quad (3)
\]

is called the radius of time window.

\[
\omega^* = \frac{1}{||\hat{\psi}(\omega)||} \int_{\mathbb{R}} \text{Re}(\hat{\psi}(\omega)) |\hat{\psi}(\omega)|^2 \, d\omega \quad (4)
\]

is the frequency window center and

\[
\Delta \omega = \frac{1}{||\hat{\psi}(\omega)||} \left[ \int_{\mathbb{R}} (\omega-\omega^*)^2 |\hat{\psi}(\omega)|^2 \, d\omega \right]^{1/2} \quad (5)
\]

is called as the radius of frequency window.

Calculate the centers and radiuses of time window and frequency window of \( \psi_{a,b}(t) \). Make use of the basic principles of wavelet function and it can be known that \( ||\psi_{a,b}(t)|| = ||\psi(t)|| = 1 \). It can be learnt from Formula (6) ~ Formula (9) that
\[
t' = \int_{\mathbb{R}} t |\psi_{a,b}(t)|^2 dt = \int_{\mathbb{R}} \frac{1}{a} |\psi(\frac{t-b}{a})|^2 dt = \int_{\mathbb{R}} (au+b) |\psi(u)|^2 du = \int_{\mathbb{R}} au |\psi(u)|^2 du + \int_{\mathbb{R}} b |\psi(u)|^2 du = a\psi_{a,b}^* + b
\]

Here in the formula, \( t' \) is the window center of \( \psi(t) \).

\[
\Delta t = \left( \int_{\mathbb{R}} (t-t')^2 |\psi_{a,b}(t)|^2 dt \right)^{1/2} = \left( \int_{\mathbb{R}} (t-a\psi_{a,b}^*-b)^2 \frac{1}{a} |\psi(\frac{t-b}{a})|^2 dt \right)^{1/2} = \left( \int_{\mathbb{R}} (au+b-a\psi_{a,b}^*-b)^2 |\psi(u)|^2 du \right)^{1/2} = \left[ a^2 \int_{\mathbb{R}} (u-t')^2 |\psi(u)|^2 du \right]^{1/2} = a\Delta \psi_{a,b}^*
\]

In this formula, \( \Delta \psi_{a,b}^* \) is the window radius of \( \psi(t) \). Similarly,

\[
\|\hat{\psi}_{a,b}(\omega)\| = \int_{\mathbb{R}} \sqrt{\lambda} \psi(\lambda \omega) e^{-i\omega t} \omega^2 d\omega = \int_{\mathbb{R}} a |\hat{\psi}(a\omega)|^2 d\omega = \|\hat{\psi}(\omega)\|
\]

Then,

\[
\omega' = \frac{1}{\|\hat{\psi}_{a,b}(\omega)\|} \int_{\mathbb{R}} \omega |\hat{\psi}_{a,b}(\omega)|^2 d\omega = \frac{1}{\|\hat{\psi}_{a,b}(\omega)\|} \int_{\mathbb{R}} \omega a |\hat{\psi}(a\omega)|^2 d\omega = \frac{1}{a} \omega_{\psi_{a,b}}^*
\]

In this formula, \( \omega_{\psi_{a,b}}^* \) is the window center of \( \hat{\psi}(\omega) \).

\[
\Delta \omega = \left( \int_{\mathbb{R}} (\omega-\omega')^2 |\hat{\psi}_{a,b}(\omega)|^2 d\omega \right)^{1/2} = \left( \int_{\mathbb{R}} (\omega - \frac{1}{a} \omega_{\psi_{a,b}})^2 a |\hat{\psi}(a\omega)|^2 d\omega \right)^{1/2} = \frac{1}{a} \Delta \omega_{\psi_{a,b}}
\]

Multiply the \( \psi_{a,b}(t) \) of compact support or rapid decline to 0 with signal \( f(t) \) and the signal \( f(t) \) can be vividly called to have opened a window. Obviously, the performance of the window affects the analytical ability on the signals. The time-frequency domain window center of function \( \psi_{a,b}(t) \) is \( (b, \frac{\omega_{\psi_{a,b}}}{a}) \). Here, \( \omega_{\psi_{a,b}} \) is the frequency of the mother wavelet function \( \psi(t) \). In the time-frequency phase plane, make the corresponding time-frequency window (a rectangle window with \( 2\Delta t \) as base and \( 2\Delta \omega \) as the height) to \( \psi_{a,b}(t) \) for any randomly fixed translation scale \( b \), its area is

\[
S_{a,b} = 2\Delta t \times 2\Delta \omega = 4a\Delta \psi_{a,b} \frac{1}{a} \Delta \omega_{\psi_{a,b}} = 4\Delta \psi_{a,b} \Delta \omega_{\psi_{a,b}} = \frac{4}{a} \Delta \omega_{\psi_{a,b}} \Delta t = S \geq 2
\]
It can be learned from the above formula that the area of the mother wavelet function $\psi(t)$ is the same as that of $\psi_{a,b}(t)$ function window and it is a fixed value. When the time window becomes broader and the frequency window smaller, this phenomenon is called Heisenberg uncertainty principle. It holds when and only when

$$\psi(t) = c e^{j\omega_0 t} = \frac{1}{2\sqrt{\pi a}} e^{-\frac{(t-b)^2}{4a}}.$$ 

The reciprocal of scale $1/a$ corresponds to the frequency $\omega$ of $\psi_{a,b}(\omega)$ to a certain extent because the basic frequency is $\omega_0/a$ and $\omega_0/a$ is the vertical coordinate of time-frequency window center. The smaller the scale is, the higher the frequency; the narrower the time window; the “thinner” the wavelet function and the faster the decline. The bigger the scale, the lower the corresponding frequency; the wider the time window, the “fatter” the wavelet function and the slower the decline. So, when processing the high-frequency signals, $\Delta\omega$ becomes bigger and when processing the low-frequency signals, $\Delta t$ becomes smaller. Such adaptive function is convenient to perform various processing on the signals.

Wavelet decomposition and reconstruction algorithm uses its characteristic of separation, performs one-dimensional wavelet transform respectively on the rows when realizing the algorithm and then completes one-dimensional wavelet transform by the column on the data after row transformation. Similar to the one-dimensional circumstance, there also exists the problem of handling the boundaries because the image signals always have finite region in practical applications \([9,10]\). The following Fig.1 is wavelet decomposition coefficient diagram.

![Fig.1. Wavelet Decomposition Coefficient Diagram](image)

3. Remote Sensing Image Denoising Based on Wavelet Adaptive Threshold Function

The algorithm steps are as follows.

1. Input the original remote sensing image. If the original remote sensing image is not grayscale image, then the original remote sensing image will be converted into gray image. If the input original remote sensing image is the grayscale image, let’s go straight to step2.

2. The image is transformed into the wavelet domain by two-dimensional wavelet transformation. Considering that the noise generally has been attenuated by 90% when it is decomposed into the third layer, and the higher the number of decomposition level is, the greater the computational complexity is and the more complex the calculation is, therefore, the selected scale is three-layer, and each sub-band image is obtained \([11]\) \([12]\).
Then the neighborhood averaging method is applied to filter the low-frequency sub-images after wavelet transform. Suppose the gray value of the image pixel is $W(j, k)$, and take it as the center, and the point set composed of window pixels is represented as $A$, and the pixel number within the point set is represented as $L$. After filtering by neighborhood averaging method, the corresponding output of the pixel is:

$$\omega(j, k) = \frac{1}{L} \sum_{(x,y) \in A} \omega(x, y)$$  \hspace{1cm} (12)

(4) Selection of threshold function
In the method of removing noise by shrinking threshold, the threshold function can be mainly divided into hard and soft threshold function.

① Hard threshold function

$$\hat{\omega}_{j,k} \leq \left\{ \begin{array}{ll} \omega_{j,k} & |\hat{\omega}_{j,k}| \geq T \\ 0 & |\hat{\omega}_{j,k}| < T \end{array} \right.$$  \hspace{1cm} (13)

② Soft threshold function

$$\hat{\omega}_{j,k} \leq \left\{ \begin{array}{ll} \text{sgn}(\omega_{j,k})(|\omega_{j,k}| - T) & |\hat{\omega}_{j,k}| \geq T \\ 0 & |\hat{\omega}_{j,k}| < T \end{array} \right.$$  \hspace{1cm} (14)

③ Improved threshold function
The high frequency sub-band image is processed by adaptive wavelet threshold, while the low frequency sub-band is not processed by threshold. Threshold formula we designed is used in the threshold selection.

$$\hat{\omega}_{j,k} \leq \left\{ \begin{array}{ll} \text{sgn}(\omega_{j,k})(|\omega_{j,k}| - T) + \frac{2T(1-\alpha)}{\exp(\omega(j,k))} & |\hat{\omega}_{j,k}| \geq T \\ 0 & |\omega_{j,k}| < T \end{array} \right.$$  \hspace{1cm} (15)

When $\alpha = 0$, the function belongs to the hard threshold; when $\alpha = 1$, the function belongs to the soft threshold. When $\alpha \in (0, 1)$, the best parameter can be screened to make the wavelet coefficient gain the optimum value.

(5) The adaptive feature threshold quantization is processed on coefficients of wavelet transform decomposition. The coefficients after threshold quantization are reconstructed by two-dimensional wavelet, and then reconstructed images are output. Hard threshold method can well retain local characteristics of image edge, but such visual distortion of the image as the ringing and pseudo gibbs effect will appear. The soft threshold method processing result is relatively smooth, but it can cause such distortion as the edge fuzzy, while, the semi-soft and semi-hard threshold function can achieve good tradeoff between hard threshold and soft threshold method by selecting appropriate threshold $T_1$ and $T_2$.

4. Simulation Results and Analysis
In order to achieve the de-noising of remote sensing images, this paper adds Gaussian white noise with mean value of 0.01 and noise variance of 0.001 to the remote sensing image, the effects of different decomposition level and different wavelet basis functions on remote sensing image de-noising are analyzed. Image de-noising is performed by median filtering, wavelet hard threshold, wavelet soft threshold and the method analyzed in this paper.

4.1. Effect of the number of wavelet decomposition level on the signal de-noising
For the remote sensing image, with Gaussian white noise, wavelet decomposition from the first level to the fourth level is respectively performed, the threshold is selected by Birge-Massart algorithm, and the wavelet soft threshold is adopted to remove noise. The simulation results are shown in Fig. 2.
Peak signal-to-noise ratio of each image after de-noising is shown in Table 1.

<table>
<thead>
<tr>
<th>De-Noising Layer</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSNR (db)</td>
<td>16.5193</td>
<td>12.5015</td>
<td>10.9193</td>
<td>9.9821</td>
</tr>
</tbody>
</table>

According to the intuitive effect map of the experiment and PSNR, level 1 wavelet decomposition of the remote sensing image has the best effect. Therefore, level 1 wavelet decomposition is selected in the following experiments.

4.2. Influence of wavelet basis function on de-noising effect

For the remote sensing image westconcordaerial (369×394) with Gaussian white noise, Sym4 wavelet, Db10 wavelet, Coif2 wavelet, Bior.4.4 wavelet, Bior.2.2 wavelet and Haar wavelet are respectively adopted to perform the wavelet soft threshold de-noising with one-level decomposition of, and the simulation results are shown in Figure 3.
Fig. 3. De-Noising of Remote Sensing Image by Different Wavelet Basis Functions

The peak signal-to-noise ratio of each image is shown in Table 2.

Table 2. De-Noising of Different Wavelet Basis Functions

<table>
<thead>
<tr>
<th>Wavelet Basis Function</th>
<th>Sym4</th>
<th>Db10</th>
<th>Coif2</th>
<th>Bior.4.4</th>
<th>Bior.2.2</th>
<th>Haar</th>
</tr>
</thead>
</table>

According to the intuitive effect map of the experiment and PSNR, Haar wavelet basis function adopted to decompose the remote sensing image has the best effect. Therefore, Haar wavelet basis function is used in the following experiments.

4.3. Different methods for remote sensing image de-noising analysis

In order to study which method can remove noise more effectively and retain the details of the image in the remote sensing image de-noising, this paper mainly compares median filtering, wavelet soft and hard threshold and the method in this paper. In the wavelet threshold de-noising, it can be seen from sections 4.1 and 4.2 that Db10 wavelet basis function is selected with the noise variance of 0.001, and the de-noising effect is best when the decomposition level is one. Below are filtering effect of median filtering, wavelet soft threshold, wavelet hard threshold and the method studied in this paper, as shown in Figure 4:
Table 3 shows the peak signal-to-noise ratio of each method:

<table>
<thead>
<tr>
<th>De-Noising Method</th>
<th>Median Filtering</th>
<th>Soft Threshold De-Noising</th>
<th>Hard Threshold De-Noising</th>
<th>The Method of This Paper</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSNR (db)</td>
<td>12.4966</td>
<td>15.9952</td>
<td>18.3176</td>
<td>20.5356</td>
</tr>
</tbody>
</table>

In order to more effectively compare the effects of different methods on remote sensing image de-noising, more effective de-noising method is adopted under appropriate circumstances. The following is the peak signal-to-noise ratio by different methods after noise variance is calculated from 0.001 to 0.009, as shown in Table 4.

<table>
<thead>
<tr>
<th>Noise Variance</th>
<th>Evaluation Criteria</th>
<th>Median Filtering</th>
<th>Soft Threshold De-Noising</th>
<th>Hard Threshold De-Noising</th>
<th>The Method of This Paper</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.001</td>
<td>PSNR</td>
<td>12.4966</td>
<td>15.9952</td>
<td>18.3176</td>
<td>20.5356</td>
</tr>
<tr>
<td>0.001</td>
<td>MSE</td>
<td>0.1674</td>
<td>0.1655</td>
<td>0.1706</td>
<td>0.1643</td>
</tr>
<tr>
<td>0.003</td>
<td>PSNR</td>
<td>12.3349</td>
<td>15.3428</td>
<td>16.9374</td>
<td>17.8162</td>
</tr>
<tr>
<td>0.003</td>
<td>MSE</td>
<td>0.2593</td>
<td>0.2541</td>
<td>0.2556</td>
<td>0.2534</td>
</tr>
<tr>
<td>0.005</td>
<td>PSNR</td>
<td>12.2277</td>
<td>14.9250</td>
<td>15.9858</td>
<td>17.1731</td>
</tr>
<tr>
<td>0.005</td>
<td>MSE</td>
<td>0.3435</td>
<td>0.3576</td>
<td>0.3354</td>
<td>0.3107</td>
</tr>
<tr>
<td>0.007</td>
<td>PSNR</td>
<td>11.1011</td>
<td>13.3829</td>
<td>14.2872</td>
<td>15.5318</td>
</tr>
<tr>
<td>0.007</td>
<td>MSE</td>
<td>0.4285</td>
<td>0.4232</td>
<td>0.4136</td>
<td>0.4142</td>
</tr>
</tbody>
</table>

Compared with the traditional threshold function, the predicted wavelet coefficients in this paper are closer to the original ones. By selecting the optimal parameter, not only the ringing and pseudo-gibbs phenomenon of
hard threshold function are largely eliminated, but also the fixed deviation in the soft threshold function is effectively controlled, so that the reconstructed signal is closer to the real signal and then the ideal de-noising effect is achieved. Through the simulation experiment, we can see the image processed by the improved algorithm is more visually clearer. By calculating the peak signal-to-noise ratio and mean square error, we can perceive that the improved algorithm is more effective in de-noising.

5. Conclusions

In this paper, the wireless sensor network system of farmland environment is used to collect real-time environmental information in the field, and send it to remote data processing center to realize real-time monitoring and spatial positioning of environmental information such as air temperature and humidity, rainfall, solar radiation and photosynthetic active radiation intensity in the field. Remote sensing images almost have the defects of low resolution and insufficient detailed information, and all remote sensing image grayscale range can't cover the range that the remote sensing sensor can reach, thus it is unfavourable for us to further research and analyze remote sensing images. Therefore, de-noising and contrast enhancement of remote sensing images is an important step for effective analysis. This paper puts forward a remote sensing image de-noising method based on wavelet adaptive threshold function. Experimental results show that such algorithm is superior to the traditional single remote sensing image de-noising algorithm in the aspects of Gaussian noise removal and image edge preservation, and with such algorithm, the image variance, signal-to-noise ratio and visual effect are improved. These real-time monitoring data are used to predict remote sensing images and invert monitoring models to ensure the accuracy of agricultural decision-making.

Acknowledgement

This work was support by “Agricultural environment monitoring system based on cloud technology and Internet of things” (Grant No. FD201601).

References