Research Article
Multimedia Image Data Compression Based on Wavelet Analysis

Rui Wang, Qi Zhu, and Weichun Bu

1College of Health Management, Fuyang Preschool Teachers College, Fuyang, Anhui 236015, China
2College of Science, Hohai University, Nanjing, Jiangsu 211100, China
3College of Science, Zhongyuan University of Technology, Zhengzhou City, Henan Province 450007, China

Correspondence should be addressed to Rui Wang; 11231410@stu.wxic.edu.cn

Received 5 July 2022; Revised 2 August 2022; Accepted 11 August 2022; Published 21 August 2022

Academic Editor: Balakrishnan Nagaraj

Copyright © 2022 Rui Wang et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

In order to improve the compression technology of multimedia image data, a compression method of multimedia image data based on wavelet analysis was proposed. By combining Fourier transform and wavelet packet multithreshold denoising method, the image data was denoised and compressed through the transform of wavelet analysis and multithreshold processing, so as to realize the compression of image data with high quality. The experimental results showed that it was effective to analyze signal singularity, singularity position, and singularity degree by using wavelet analysis. And the signal mutation position near $t = 0$ could be seen clearly from the wavelet coefficient diagram, while the Fourier transform diagram did not provide any information about when the frequency mutation occurred. It was concluded that the method of multimedia image data compression based on wavelet analysis could promote the development of multimedia image data compression technology effectively.

1. Introduction

The amount of multimedia image data is very large after digital processing. If the data is not compressed, the computer system cannot store and exchange it. Therefore, how to effectively store and transmit the image data in the multimedia system becomes one of the biggest problems faced by the multimedia personal computer (MPC). Data compression is an important way to solve this problem.

Wavelet analysis is an applied mathematical theory developed in the 1980s. It has obtained many important applications in many fields of surveying and mapping. An automatic cartographic synthesis model based on wavelet analysis is established to test the river network data [1]. These researches have achieved good results, but the depth and breadth of the research are not enough, and there are still many problems to be further investigated, but it is undeniable that wavelet analysis is an ideal mathematical tool for signal processing. As a means of signal processing, wavelet analysis has been more and more important for theoretical workers and engineers. And it has obtained the remarkable effect in many applications. Compared with the traditional processing method, there is a qualitative leap. It proves that the wavelet analysis technology, as a harmonic analysis method, has the huge vitality and broad application prospects, as shown in Figure 1.

2. Literature Review

Data compression refers to the technology of reencoding the original data to remove the redundancy in the original data and represent the original data with a small amount of data, which is the premise of processing image, audio, video, and other media data on the computer. With the development of computer network and computer communication technology, the data compression technology has received unprecedented attention and popularized and developed rapidly.

The compressed coding theory was first proposed in 1948. Oliver proposed the PCM (pulse code modulation) coding theory [2, 3]. From the perspective of the development of data compression technology, it could be divided into two important stages. The first stage was before 1984, in which the main theory was to study the basis of data compression. The second phase was from 1985 to now, and it walked into the practical phase of data compression technology. In 1988, the data
Transform coding is a kind of lossy coding. The so-called transform coding refers to the mathematical transform of the original time or space domain of the original data to highlight important parts of the original data after transform, so as to focus on processing [4]. At present, it is widely used in monochrome image, color image, still image, moving image, and multimedia computer technology in TV image compression within frames and between frames.

Transform coding refers to the transform of a given image to another data domain (transform domain or frequency domain) in order to represent a large amount of information with less data. In other words, it does not directly encode spatial domain image signals but first maps the currently expressed spatial domain image signals to another orthogonal vector space through transform to obtain a series of transform coefficients which are encoded then [5]. The coding accuracy of the important coefficients in the transform domain is higher than that of the second important coefficients. Transform itself is a lossless and reversible technology, but in order to obtain better coding effect, some unimportant coefficients are ignored; so, it becomes a lossy technology. Commonly used transform coding schemes include discrete cosine transform (DCT) and Fourier transform coding [6, 7].

In the DCT transform coding algorithm, the original image is usually divided into subblocks of $8 \times 8$ size, and each subblock performs DCT forward transform in sequence, quantizes the DCT transform coefficient, and then carries out coding. The decoding process is the opposite of the coding process; that is, the first is decoding and then dequantization. DCT inverse transform is performed on each subblock to obtain subblock image, and each subblock is carried out in sequence to obtain the image restored after decoding. DCT is widely used in image compression.

After DCT forward transform, most of the energy is concentrated in the upper left corner of the $Y$ matrix, which means that the correlation of the image decreases after DCT transform, so that fewer bits can be used to encode the upper left corner element of matrix $D$, thus achieving the purpose of data compression.

Wavelet analysis is a new field which is rapidly developing in current mathematics. It has both profound theory and extensive application. Compared with Fourier transform and Gabor transform, it is a local transform of time and frequency. So, it can effectively extract information from signals and perform multiscale analysis on functions or signals by scaling and shifting operations. Wavelet transform has solved many problems that Fourier transform could not solve; so, it is known as the "mathematical microscope" and is a landmark progress in the development history of harmonic analysis [8].

In the research, data compression of multimedia image was processed based on wavelet analysis. Wavelet analysis could achieve higher compression ratio and higher reproducibility image compression in image data compression. Therefore, wavelet analysis could be used to compress multimedia image data more efficiently and achieve better results.

3. Research Methods

3.1. Fourier Transform. Fourier transform ($FT$) is one of the important application tools in many scientific fields. Mathematically, it is the conversion of a complex operation on one function into a simpler operation on another function. Fourier transform transforms one function $F(t)(-\infty < t < \infty)$ into another function $F(\omega)(-\infty < \omega < \infty)$ by means of integration, as shown in Formula (1).

$$FT : f(t) \rightarrow F(\omega) = \int_{-\infty}^{\infty} f(t) e^{i\omega t} \, dt. \quad (1)$$

When $f(t)$ meets the appropriate conditions, it has the contravariant transform ($FT^{-1}$), as shown in Formula (2).

$$FT^{-1} : F(\omega) \rightarrow f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega) e^{i\omega t} \, d\omega. \quad (2)$$

The FT transform transforms the derivative of $f(t)$ into the multiplication of $F(\omega)$, $(d/dt)f(t) \rightarrow i\omega F(\omega)$ and transforms the two functions the convolution of two functions $f(t)$ with $g(t)$ into the multiplication of $F(\omega)$ with $g(\omega)$. Most of
the analysis and processing of signals uses linear constant coefficient differential operators or convolution operators to describe the relationship between the inputs and outputs. It is much simpler to study the relationship between the input and output spectrum of such signals than to directly study the signal itself, that is, from the frequency domain characteristics [9]. Fourier transform is the time domain and frequency domain mutual conversion tool. From a physical sense, the essence of the Fourier transform is to decompose this waveform in the time domain into a superposition of many sine waves of different frequencies. So, the study of the function $f(t)$ can be translated into the study of its weight, namely, Fourier transform $F(\omega)$.

By the definition of the Fourier transform, $F(\omega)$ depends on the global properties of $f(t)$ along the real axis $(-\infty, \infty)$; so, it does not reflect the local time range of the signal, that is, for a particular frequency in the Fourier spectrum, when that frequency is generated cannot be known. And in many practical problems, what people are interested in is the characteristics of the signal in the local time range. To address this weakness, Gabor puts forward the concept of "window Fourier transform" in 1946, also known as short-time Fourier transform (STFT) [10]. The basic idea of window Fourier transform is to divide the signal into many small time intervals and analyze each time interval with Fourier transform in order to determine the frequency existing in this time interval. The approach is to introduce a smooth function $g(t)$, called the window function, which is identical to 1 on the interval $(-\Delta + \delta, \Delta - \delta)$ and rapidly decreases smoothly from 1 to 0 on the interval $(-\Delta - \delta, -\Delta + \delta)$ and $(\Delta - \delta, \Delta + \delta)$ ($\delta$ is a suitably small positive number). Multiplying $f(t)$ by $g(t-\tau)$ is equivalent to opening a $2\Delta$ window centered on $t = \tau$.

The window Fourier transform formula of function $f(t)$ on window function $g(t-\tau)$ is Formula (3).

$$G_j(\omega, \tau) = \int_{-\infty}^{\infty} F(t)g(t-\tau)e^{-j\omega t} \, dt. \quad (3)$$

$G(\omega, \tau)$ reflects the spectral characteristics of signal $f(t)$ near $t = \tau$, and its inversion formula is Formula (4).

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} d\omega \int_{-\infty}^{\infty} e^{j\omega t}g(t-\tau)G_j(\omega, \tau) \, d\tau. \quad (4)$$

The window position of STFT changes with $\tau$, which meets the requirements of studying the local nature of different positions of signals. However, the size and shape of its window function remain unchanged regardless of time and frequency, which cannot meet the requirements of variable window processing when processing time-varying signals. In order to solve this problem, a new time-frequency analysis theory, the wavelet transform, was developed in the late 1980s on the basis of inheriting and developing the localization idea of STFT.

The so-called wavelet transform is to obtain a subwavelet (also known as wavelet base) $\psi_{ab}(t) = (1/\sqrt{a})\psi(1-b/a)$ after the independent variable $t$ of a function $\psi(t)$ is shifted (b) and stretched (a) [11]. The $W_f(a, b)$, a function with double parameters $a$ and $b$, was obtained by the inner product of the function $f(t)$, as shown in Formula (5).

$$W_f(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-b}{a}\right) \, dt, \quad a > 0. \quad (5)$$

The mother wavelet $\psi(t)$ has a compact support set [12]. That is, $\psi(t)$ is equal to 0 or rapidly approaches 0 outside the finite interval (making it play the role of a window). It is ensured that $\int_{-\infty}^{\infty} \psi(t) \, dt = 0$ (so that its function values alternate with positive and negative fluctuations). The position of the window moves with $\int_{-\infty}^{\infty} \psi(t) \, dt = 0$, and the window shrinks with $a$. Integral Formula (5) can be transformed into convolution form; so, the wavelet transform is to filter the $f(t)$ in the window, and this filtering is a band-pass filtering. The larger $a$ is, the narrower the band is and the lower the average frequency is. It is as if a man was watching a scene, and the farther he stood, the greater the window, and the more obscure the scene. Conversely, the smaller $a$ is, the higher the resolution is. This is multiresolution analysis, known as the "mathematical microscope" [13].

The data quality of wavelet transform is to project the signal onto a series of wavelet bases (a series of wavelet basis functions are used to approximate the signal), which is generally divided into continuous (CWT) and discrete (DWT) wavelet transform [14, 15].

The process of continuous wavelet transform (CWT) can be understood as follows. The wavelet with a certain scale $a$ is selected, and it is compared with the left end alignment of the original signal. According to the continuous wavelet transform formula, see Formula (6).

$$CWT = \int_{-\infty}^{\infty} f(t)\psi_{ab}(t) \, dt. \quad (6)$$

Calculate the similarity coefficient of the two functions and then move the wavelet function to the right one wavelet function distance for comparison and calculation, until the whole signal operation is completed. The wavelet scale parameter $a$ is changed to repeat the above process. This results in wavelet coefficient at a range of scales. Finally, the gray scale of wavelet coefficients can be made by taking time as abscissa and scale as ordinate. Taking Morlet wavelet as an example to transform the function $f(t)$, when $-1 < t < 0$ and $f(t) = \sin(50t)$. When $0 < t < 1$, $f = \sin(100t)$. It can be clearly seen from the wavelet coefficient diagram that the position of signal mutation is near $t = 0$, while the Fourier transform diagram does not provide any information about when the frequency mutation occurs.

### 3.2. Key Technologies of Wavelet Packet Multithreshold Denoising Method

Image denoising refers to the process of reducing the noise in digital images. In the process of digitalization and transmission, the digital image in reality is often affected by the noise interference of imaging equipment and external environment, which is called noise-containing image or noise image. Noise is an important cause of image...
interference. So, in order to better compress the digital image, it is necessary to carry out the denoising processing. Wavelet packet multithreshold denoising method is a good denoising method [16]. The mathematical expressions of the decomposition algorithm and reconstruction algorithm of wavelet packet theory are as follows.

The decomposition algorithm of wavelet packet is that \( f_{d_j,2^k} \) and \( f_{d_j,2^{k+1}} \) are solved through \( f_{d_j,2^{k+1}} \), as shown in Formula (7).

\[
\begin{align*}
\delta_{d_j,2^k} &= \sum_p h_{p-2}d_{p}^{j+2k} \\
\delta_{d_j,2^{k+1}} &= \sum_p g_{p-2}d_{p}^{j+1}
\end{align*}
\tag{7}
\]

The reconstruction algorithm of wavelet packet is that \( \{d_t^{j+1,k}\} \) is solved by \( \{d_t^{2k}\} \) and \( \{d_t^{2k+1}\} \).

\[
\delta_{d_t}^{j+1,k} = \sum_p \left(h_{1-2p}d_{p}^{2k} + g_{1-2p}d_{p}^{2k+1}\right)
\tag{8}
\]

In Formula (8), \( h \) and \( g \) are the filter coefficient. \( d \) is the wavelet packet decomposition coefficient, \( p \) and \( t \) are the decomposition layer number, and \( j \) and \( k \) are the node number of the wavelet packet.

The distribution of noise in the frequency domain is mainly concentrated in the higher frequency part. Therefore, when using wavelet packet to denoise, if the same threshold processing method is adopted in different frequency band information, or different threshold processing methods are adopted in the same frequency band information, the denoising accuracy will be affected. So, how to divide frequency band accurately is the key problem of multithreshold denoising. In the research, a classification method is proposed, which is based on frequency order and information type reorganization. According to the theory of wavelet packet transform, it can extract useful information hidden in low frequency, medium frequency, and high frequency. Taking three layers as an example, signal decomposition is shown in Figure 2. The GPS deformation monitoring data with sampling frequency of 2 Hz is taken as an example, and Nyquist sampling theorem is applied [17]. The signal is divided into wavelet packets as shown in Figure 3. Then, each node of the wavelet packet tree at the third layer is corresponding to Figure 2 one by one, and Table 1 is obtained.

Table 1 shows that the natural order and frequency order of nodes in wavelet packet tree are inconsistent. The lowest frequency part corresponds to the first node, and the highest frequency part corresponds to the fifth node. The reason for this phenomenon is that the high-pass filter will carry out a “flip” operation when the wavelet packet is decomposed. It can be proved by the properties of wavelet packet that the decomposition of any wavelet packet will produce the phenomenon of inconsistency between natural order and frequency order, and the situation of inconsistency is the same. Therefore, when the wavelet packet decomposes each layer, the low-frequency decomposition part is arranged in ascending order of frequency, and the high-frequency part
is arranged in ascending order of frequency. In the field of deformation monitoring, because noise distribution is closely related to frequency order, frequency order rather than natural order is needed.

In the deformation analysis, there are often frequency bands that need to be preserved and denoised centrally, if the vibration frequency information of the building owner mode of 0.15 Hz needs to be monitored; according to the calculation, [3, 0] and [1, 3] are the concentrated frequency band of useful information, namely, the low frequency band. However, noise pollution is general. [3 and 4] are the frequency band of useless information concentration, that is, the high frequency band. The other nodes are transitional frequency band, that is, middle frequency band. Therefore, the wavelet packet decomposition coefficients can be grouped according to the frequency bands to be monitored and the situation of noise pollution, which is the method of reorganization according to the information type. Specifically, according to the distribution of signal and noise, taking three layers as an example, \( \alpha \) is the proportion coefficient of low frequency band, \( \beta \) is the proportion coefficient of high frequency band, and \( n \) is the number of signal decomposition layers. Then, there is a wavelet packet tree node grouping. It should be pointed out that in some special cases, the frequency band can be further subdivided into low frequency, sublow frequency, intermediate frequency, subhigh frequency, and high frequency, but the basic principle remains the same.

In Table 1, wavelet packet tree nodes \([n, m_0], [n, m_1], \ldots, [n, m_{2^n-1}]\) are arranged in order of frequency from smallest to largest.

3.3. Multithreshold Processing of Wavelet Packet Decomposition Coefficients. Because the distribution of signal and noise is not fully considered in the single threshold criterion, it is easy to have insignificant or excessive denoising effect in denoising, while the multithreshold criterion can overcome the above shortcomings well [18]. The basic idea of multithreshold criterion is to flexibly select different threshold criteria for each wavelet packet decomposition coefficient according to certain rules, so as to retain useful information to the maximum extent and remove useless information. The four threshold criterion commonly used in wavelet packet analysis includes fixed-form threshold criteria (sqtwolog), adaptive threshold criteria (rigrsure), heuristic threshold criteria (heursure), and minimaxi [19]. Due to the different selection rules, the denoising effect is different. Therefore, each wavelet packet decomposition coefficient has its most appropriate threshold criteria [20].

The four threshold criterion has their own characteristics. Among them, sqtwolog threshold criteria and heursure threshold criteria are similar in that all coefficients are processed; so, noise can be strongly removed. Correspondingly, it is easy to over-denoise; so, it can be called “radical” denoising criteria, which is suitable for processing the high frequency part of GPS signal [21, 22]. Rigrsure threshold criteria and minimaxi threshold criteria deal with part of the coefficient, which is a relatively compromise processing method. Therefore, it can prevent excessive denoising. Correspondingly, it is prone to the phenomenon of not obvious denoising; so, it can be called “conservative” denoising criteria, suitable for dealing with the low-frequency part. Among them, rigrsure threshold criteria and minimaxi threshold criteria are more suitable for middle frequency band. Therefore, the selection table of multithreshold criteria as shown in Table 2 is established for threshold processing of wavelet packet decomposition coefficients [23].

### 4. Result Analysis

A signal can be decomposed by the wavelet transform, and then the original signal can be obtained through the reconstruction. Figure 4 is a schematic diagram of a fault signal decomposed and reconstructed by algorithm. From the low-frequency coefficients in the figure, it can be clearly seen in the “approximate signals” of the original signal at different scales. The rough outline of the signal is preserved, while the high frequencies reflect the turning points of the signal clearly. Singular value detection is carried out on the basis of the algorithm. The singular point and irregular mutation part of the signal often carry important information, which is an important part of the signal. Image compression processing is of great significance [24]. For a long time, the Fourier transform is the main tool to study the singularity of functions. Its method is to study the attenuation of functions in the Fourier transform domain to infer whether the function has the singularity and the magnitude of the singularity. However, Fourier transform lacks spatial locality. It can only determine the global properties of the singularity of a function, but it is
difficult to determine the position and distribution of the singularity in space. However, the wavelet transform has the property of spatial localization, and the wavelet coefficient diagram can clearly reflect that the location of signal mutation near $t = 0$, while the Fourier transform diagram does not provide any information about when the frequency mutation occurs. Therefore, it is effective to use wavelet to analyze signal singularity, singularity position, and singularity degree [25].

5. Conclusions

In the research, the multimedia data image compression method based on wavelet analysis is used for compression processing. When using the wavelet analysis method to compress data image, the compression ratio is high, the compression speed is fast, and the basic characteristics of signal and image can be kept unchanged after compression and can be anti-interference in the transmission process. The wavelet packet multithreshold denoising method is better than traditional wavelet, wavelet packet denoising method, and other improved wavelet packet denoising method. It provides an optimization method for the compression of multimedia image data.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] Y. Zhu, G. Li, R. Wang, S. Tang, and K. Cao, "Intelligent fault diagnosis of hydraulic piston pump based on wavelet analysis and improved alexnet," Sensors, vol. 21, no. 2, article 549, 2021.

[2] S. Yarlagadda, S. Kaza, A. C. Tummala, E. V. Babu, and R. Prabhakar, "The reduction of crosstalk in vlsi due to parallel bus structure using data compression bus encoding technique implemented on artix 7 fpga architecture 1," Journal of Information Technology, vol. 9, no. 1, pp. 456–460, 2021.

[3] Z. B. Khanian and A. Winter, "Distributed compression of correlated classical-quantum sources or: the price of ignorance," IEEE Transactions on Information Theory, vol. 66, no. 9, pp. 5620–5633, 2020.

[4] X. Zhao, S. H. Kim, Y. Zhao et al., "Transform coding in the vvc standard," IEEE Transactions on Circuits and Systems for Video Technology, vol. 31, no. 10, pp. 3878–3890, 2021.

[5] Q. Yu, M. Kavitha, and T. Kurita, "Autoencoder framework based on orthogonal projection constraints improves anomalies detection," Neurocomputing, vol. 450, no. 1, pp. 372–388, 2021.

[6] A. D. Hangkawidjaja, A. Prijono, and J. Suherman, "Discrete cosine transform and multi class support vector machines for classification cardiac atrial arrhythmia and cardiac normal," Journal of Physics: Conference Series, vol. 1858, no. 1, article 012093, 2021.

[7] S. M. Abrarov, R. Siddiqui, R. K. Jagpal, and B. M. Quine, "A rational approximation of the fourier transform by integration with exponential decay multiplier," Applied Mathematics, vol. 12, no. 11, pp. 947–962, 2021.

[8] C. D. Grave, L. Pipia, B. Siegmann, P. Morcillo-Pallarés, and J. Verrelst, "Retrieving and validating leaf and canopy chlorophyll content at moderate resolution: a multiscale analysis with the sentinel-3 olic sensor," Remote Sensing, vol. 13, no. 8, article 1419, 2021.

[9] P. Gangsar, R. K. Pandey, and M. Chouksey, "Unbalance detection in rotating machinery based on support vector machine using time and frequency domain vibration features," Noise & Vibration Worldwide, vol. 52, no. 4-5, pp. 75–85, 2021.

[10] B. Li, Z. Jiang, and J. Chen, "On performance of sparse fast fourier transform algorithms using the flat window filter," Access, vol. 8, pp. 79134–79146, 2020.
[11] A. Winursito, F. Arifin, A. Nasuha, and A. S. Priambodo, “Design of robust heart abnormality detection system based on wavelet denoising algorithm,” Journal of Physics: Conference Series, vol. 2111, no. 1, article 012048, 2021.

[12] L. Asimopolos, N. S. Asimopolos, and A. A. Asimopolos, “Wavelet analyses of geomagnetic data regarding major geomagnetic disturbances,” Journal of Environmental Science and Engineering, vol. 10, no. 1, pp. 31–39, 2021.

[13] J. B. Stückrath and F. A. Bischoff, “Reduction of hartree–fock wavefunctions to kohn–sham effective potentials using multi-resolution analysis,” Journal of Chemical Theory and Computation, vol. 17, no. 3, pp. 1408–1420, 2021.

[14] T. Triadi, I. Wijayanto, and S. Hadiyoso, “Electrooculogram (eog) based mouse cursor controller using the continuous wavelet transform and statistic features,” Lontar Komputer Jurnal Ilmiah Teknologi Informasi, vol. 12, no. 1, p. 53, 2021.

[15] H. K. Bhagya and N. Keshaveni, “Contrast enhancement technique using discrete wavelet transform with just noticeable difference model for 3d stereoscopic degraded video,” International Journal of Innovative Technology and Exploring Engineering, vol. 10, no. 3, pp. 7–13, 2021.

[16] H. H. Maria, A. M. Jossy, G. Malarvizhi, and A. Jenitta, “Analysis of lifting scheme based double density dual-tree complex wavelet transform for de-noising medical images,” Optik - International Journal for Light and Electron Optics, vol. 241, no. 11, article 166883, 2021.

[17] R. Arie, A. Brand, and S. Engelberg, “Compressive sensing and sub-nyquist sampling,” IEEE Instrumentation and Measurement Magazine, vol. 23, no. 2, pp. 94–101, 2020.

[18] K. Zhang, X. N. Li, Z. Y. Song, J. Y. Yan, and J. C. Yin, “Human health risk distribution and safety threshold of cadmium in soil of coal chemical industry area,” Minerals, vol. 11, no. 7, article 678, 2021.

[19] T. Gr Eve, L. Wang, N. Thon, C. Schichor, and A. Szélényi, “Prognostic value of a bilateral motor threshold criterion for facial corticobulbar mep monitoring during cerebellopontine angle tumor resection,” Journal of Clinical Monitoring and Computing, vol. 26, no. 4, p. 26, 2020.

[20] Y. Wang, W. Wang, M. Zhou, A. Ren, and Z. Tian, “Remote monitoring of human vital signs based on 77-ghz mm-wave fmcw radar,” Sensors, vol. 20, no. 10, p. 2999, 2020.

[21] M. Fan and A. Sharma, “Design and implementation of construction cost prediction model based on svm and lssvm in industries 4.0,” International Journal of Intelligent Computing and Cybernetics, vol. 14, no. 2, pp. 145–157, 2021.

[22] J. Jayakumar, S. Chacko, and P. Ajay, “Conceptual implementation of artificial intelligence based E-mobility controller in smart city environment,” Wireless Communications and Mobile Computing, vol. 2021, article 5325116, 8 pages, 2021.

[23] L. Li, Y. Diao, and X. Liu, “Ce-Mn mixed oxides supported on glass-fiber for low-temperature selective catalytic reduction of NO with NH3,” Journal of Rare Earths, vol. 32, no. 5, pp. 409–415, 2014.

[24] P. Ajay, B. Nagaraj, R. A. Kumar, R. Huang, and P. Ananthi, “Unsupervised hyperspectral microscopic image segmentation using deep embedded clustering algorithm,” Scanning, vol. 2022, Article ID 1200860, 9 pages, 2022.

[25] G. Veselov, A. Tselykh, A. Sharma, and R. Huang, “Special issue on applications of artificial intelligence in evolution of smart cities and societies,” Informatica, vol. 45, no. 5, article 603, 2021.