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Research Article

A Wavelet-Based Robust Relevance Vector Machine Based on Sensor Data Scheduling Control for Modeling Mine Gas Gushing Forecasting on Virtual Environment

Wang Ting,[1] Cai Lin-qin,[1] Fu Yao,[2] and Zhu Tingcheng[2]

[1] *Key Laboratory of Industrial Internet of Things & Networked Control, Ministry of Education, Chongqing University of Posts and Telecommunications, Chongqing 400065, China*
[2] *Institute of Grassland Science, Key Laboratory of Vegetation Ecology, Ministry of Education, Northeast Normal University, Changchun 130024, China*

Correspondence should be addressed to Wang Ting; wwangting2013@163.com

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It is wellknown that mine gas gushing forecasting is very significant to ensure the safety of mining. A wavelet-based robust relevance vector machine based on sensor data scheduling control for modeling mine gas gushing forecasting is presented in the paper. Morlet wavelet function can be used as the kernel function of robust relevance vector machine. Mean percentage error has been used to measure the performance of the proposed method in this study. As the mean prediction error of mine gas gushing of the WRRVM model is less than 1.5%, and the mean prediction error of mine gas gushing of the RVM model is more than 2.5%, it can be seen that the prediction accuracy for mine gas gushing of the WRRVM model is better than that of the RVM model.

1. Introduction

It is wellknown that mine gas gushing forecasting is very significant to ensure the safety of mining [1–3]. The study results elaborate that the influencing factors of mine gas gushing mainly include buried depth of coal seam, thickness of coal seam, gas content of coal seam, distance of coal seam, daily advance, and day output [4–6]. Artificial neural networks [7–9] have been applied to mine gas gushing forecasting. However, the forecasting results of artificial neural networks are poor due to their shortcomings including over-fitting and local maximum.

A wavelet-based robust relevance vector machine based on sensor data scheduling control for modeling mine gas gushing forecasting is presented in this paper. Relevance vector machine is a kind of improved support vector machine [10–14], which is based on a Bayesian framework. Morlet wavelet function can be used as the kernel function of robust relevance vector machine.

In the study, the experimental data are employed to study the prediction ability for mine gas gushing. The five factors including buried depth of coal seam, thickness of coal seam, lithology of roof, thickness of bed rock, and ratio of sand and rock are used as the input features of the WRRVM model, and mine gas gushing is used as the output of the WRRVM model. Before the training samples are created, the experimental data must be normalized. Then, the training samples are created. Mean percentage error has been used to measure the performance of the proposed method in this study. As the mean prediction error of mine gas gushing of the WRRVM model is less than 1.5%, and the mean prediction error of mine gas gushing of the RVM model is more than 2.5%, it can be seen that the prediction accuracy for mine gas gushing of the WRRVM model is better than that of the RVM model.

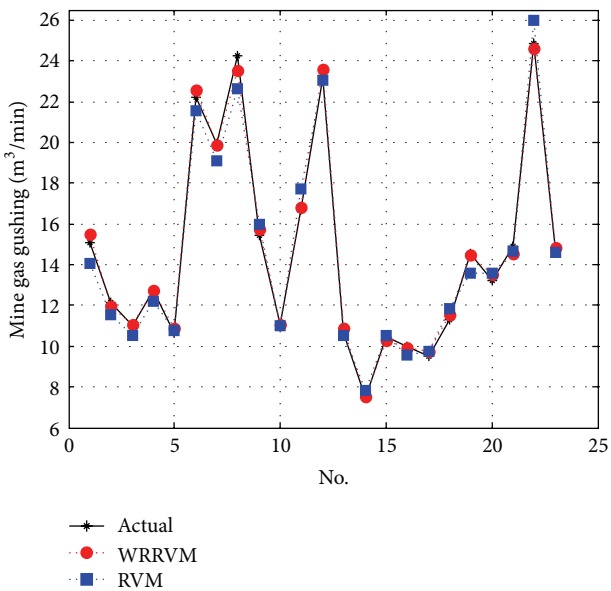

FIGURE 1: The comparison of the prediction values of mine gas gushing between the WRRVM model and the RVM model trained by the five input features.

Therefore, the WRRVM model is very suitable for mine gas gushing prediction.

2. Wavelet-Based Robust Relevance Vector Machine

The regression function of relevance vector machine can be described as follows:

$$f(x) = \sum_{i=1}^{n} w_i \phi(x_i), \tag{1}$$

where w_i is the weights and $\phi(\cdot)$ is the mapping function.

Given the vector $R = [r_1, r_2, \ldots, r_n]^T$, the likelihood function of the dataset can be obtained as follows:

$$\begin{aligned} p(t \mid w, r, \sigma^2) &= \left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^n \sqrt{|P|} \\ &\quad \times \exp\left\{-\frac{1}{2\sigma^2}(t - \eta w)' P (t - \eta w)\right\}, \\ p(w \mid t, \alpha, r, \sigma^2) &= \frac{p(w \mid \alpha)\, p(t \mid w, r, \sigma^2)}{p(t \mid \alpha, r, \sigma^2)} = N(w \mid \lambda, \Delta), \end{aligned} \tag{2}$$

where $P = \mathrm{diag}(r_1, r_2, \ldots, r_n)$, Δ is the variance matrix, and λ is the mean value vector, which can be described as follows:

$$\begin{aligned} \Delta &= \left(A + \sigma^{-2} \sum_{i=1}^{n} r_i \phi(x_i) \phi(x_i)'\right)^{-1}, \\ \lambda &= \sigma^{-2} \Delta \left(\sum_{i=1}^{n} r_i \phi(x_i) t_i\right). \end{aligned} \tag{3}$$

Then, the marginal likelihood function of robust relevance vector machine can be obtained as follows:

$$\begin{aligned} &p(t \mid \alpha, r, \sigma^2) \\ &= \int p(t \mid w, r, \sigma^2)\, p(w \mid \alpha)\, dw \\ &= \frac{(1/\sqrt{2\pi})^n}{\sqrt{|\sigma^2/B + \eta A^{-1} \eta'|}} \exp\left\{-\frac{1}{2} t' \frac{1}{|\sigma^2/B + \eta A^{-1} \eta'|} t\right\}. \end{aligned} \tag{4}$$

In this study, Morlet wavelet function can be used as the kernel function of robust relevance vector machine, which can be described as follows [15, 16]:

$$k(x, x') = \prod_{i=1}^{m} \cos\left(1.75 \times \frac{x - x'}{a_i}\right) \exp\left(-\frac{\|x - x'\|^2}{2a_i^2}\right). \tag{5}$$

It is sufficient to prove the inequality:

$$F[x](w) = (2\pi)^{-m/2} \int \exp(-j(w \cdot x))\, k(x)\, dx \geq 0, \tag{6}$$

where

$$k(x) = \prod_{i=1}^{m} \cos\left(\frac{1.75x}{a_i}\right) \exp\left(-\frac{\|x\|^2}{2a_i^2}\right). \tag{7}$$

3. Experimental Analysis for Mine Gas Gushing Forecasting Based on Wavelet-Based Robust Relevance Vector Machine

In this section, the experimental data are employed to study the prediction ability for mine gas gushing of the proposed wavelet-based robust relevance vector machine. The five factors including buried depth of coal seam, thickness of coal seam, lithology of roof, thickness of bed rock, and ratio of sand and rock are used as the input features of the WRRVM model, and mine gas gushing is used as the output of the WRRVM model.

Figure 1 gives the comparison of the prediction values of mine gas gushing between the WRRVM model and the RVM model trained by the five input features including buried depth of coal seam, thickness of coal seam, lithology of roof, thickness of bed rock, and ratio of sand and rock; Figure 2 gives the comparison of the prediction values of mine gas gushing between the WRRVM model and the RVM model trained by the four input features including buried depth of coal seam, thickness of coal seam, lithology of roof, and thickness of bed rock; Figure 3 gives the comparison of the prediction values of mine gas gushing between the WRRVM model and the RVM model trained by the four input features including buried depth of coal seam, thickness of coal seam, lithology of roof, and ratio of sand and rock; Figure 4 gives the comparison of the prediction values of mine gas gushing between the WRRVM model and the RVM model trained by

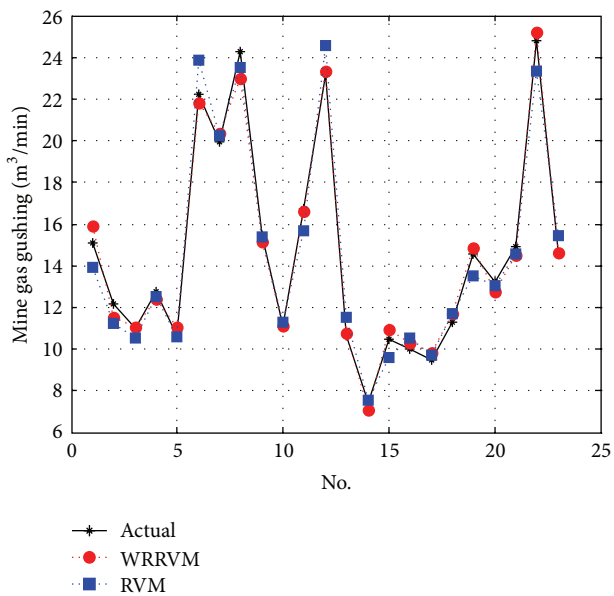

Figure 2: The comparison of the prediction values of mine gas gushing between the WRRVM model and the RVM model trained by the four input features including buried depth of coal seam, thickness of coal seam, lithology of roof, and thickness of bed rock.

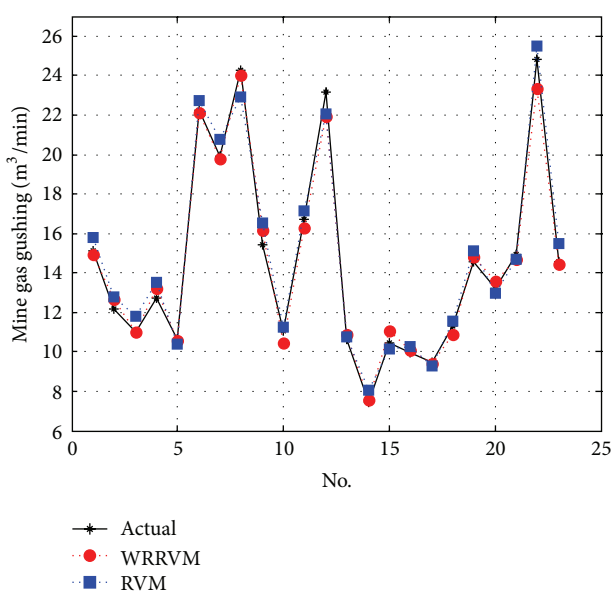

Figure 3: The comparison of the prediction values of mine gas gushing between the WRRVM model and the RVM model trained by the four input features including buried depth of coal seam, thickness of coal seam, lithology of roof, and ratio of sand and rock.

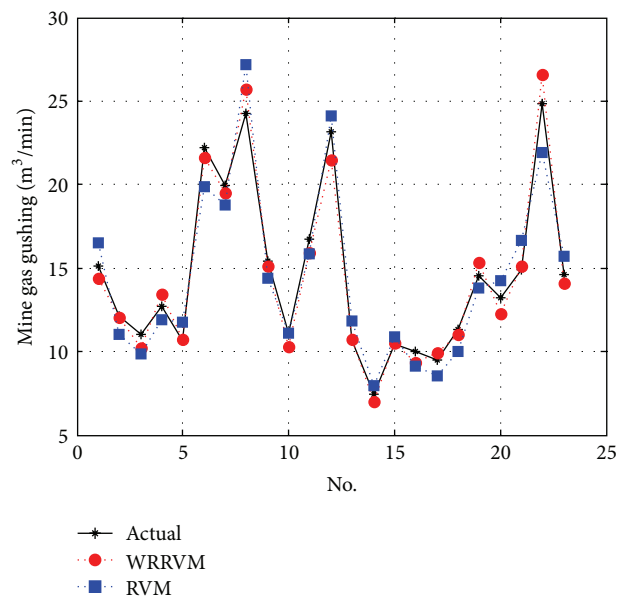

Figure 4: The comparison of the prediction values of mine gas gushing between the WRRVM model and the RVM model trained by the three input features including buried depth of coal seam, thickness of coal seam, and lithology of roof.

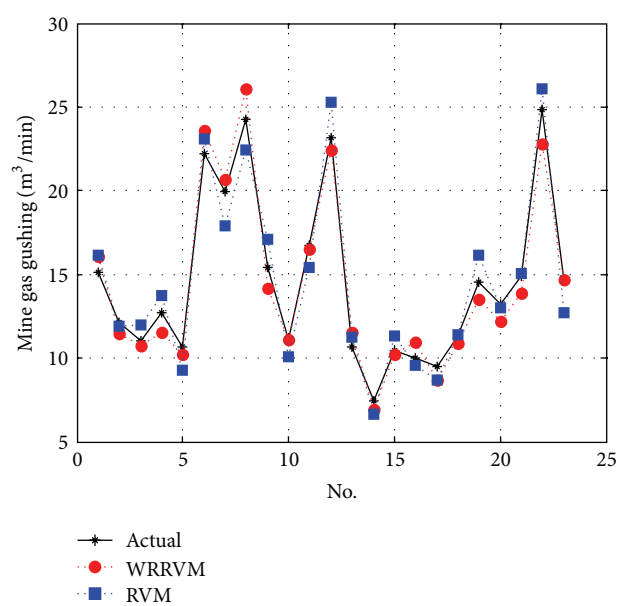

Figure 5: The comparison of the prediction values of mine gas gushing between the WRRVM model and the RVM model trained by the three input features including buried depth of coal seam, thickness of coal seam, and ratio of sand and rock.

the three input features including buried depth of coal seam, thickness of coal seam, and lithology of roof; Figure 5 gives the comparison of the prediction values of mine gas gushing between the WRRVM model and the RVM model trained by the three input features including buried depth of coal seam, thickness of coal seam, and ratio of sand and rock. Mean percentage error has been used to measure the performance of the proposed method in this paper. As the mean percentage prediction error of mine gas gushing of the WRRVM model is less than 1.5%, and the mean percentage prediction error of mine gas gushing of the RVM model is more than 2.5%, it can be seen that the prediction accuracy for mine gas gushing of the WRRVM model is better than that of the RVM model.

4. Conclusion

A wavelet-based robust relevance vector machine based on sensor data scheduling control for modeling mine gas gushing forecasting is presented in the paper. Morlet wavelet function can be used as the kernel function of robust relevance vector machine. As the mean prediction error of mine gas gushing of the WRRVM model is less than 1.5%, and the mean prediction error of mine gas gushing of the RVM model is more than 2.5%, it can be seen that the prediction accuracy for mine gas gushing of the WRRVM model is better than that of the RVM model. Therefore, the WRRVM model is very suitable for mine gas gushing prediction.

Acknowledgments

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