Water Leakage Detection Based on Variation Bayesian Neural Network Autoencoder

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Abstract. Water pipe leakage detection is of great significance to the protection of water resources in our country. However, the detection accuracy of water pipe vibration signals is easily affected by external noise. Existing detection technologies are difficult to reduce the influence of noise signals, and some machine learning based outlier detection models are not very robust. Variation Bayesian neural network Autoencoder (VBAE) replaces the fully connected layer network in encoder and decoder with Bayesian neural network (BNN) on the basis of Variation Autoencoder (VAE). VAE has a strong generalization ability, while BNN has an uncertainty quantification ability. VBAE combines the advantages of the two models and is very robust. Experiments have proved that, compared with other models, VBAE for water leakage detection can greatly reduce the influence of noise on the output of the model, and has a better detection effect.

1. Introduction

Country's water supply pipelines are extremely large and complex. The total length of the pipelines in service is nearly one million kilometers and there are a large number of cases where the service time exceeds the prescribed time. The water supply pipeline network is corroded seriously and there are a large number of leaks. Therefore, accurate water leakage detection is of great significance to water resources conservation. Regarding pipeline leakage detection research, researchers have proposed a series of solutions. The traditional passive detection methods have a long time delay, and researchers are more researching active detection methods.

The popular detection method is to collect the water pipe vibration signals by using related instrument detection equipment, and perform fast Fourier transformation (FFT) on the time sequence signals to obtain the spectrum information of the signals[1-2]. According to whether the frequency corresponding to the curve peak is in the frequency range of leakage signals, researchers can determine whether the water pipe is leaking. The disadvantage of this method is that the collected signals need to be converted into spectrum signals, and the spectrum signals are easily interfered by noise signals caused by the external environment, and a series of complex filtering algorithms are required to obtain ideal spectrum signals. In addition, machine learning is now widely used in the field of industrial engineering. Some researchers input the water pipe vibration signals into artificial neural network (ANN) or Support Vector Machine (SVM) to train the signals to achieve classification and water leakage detection [3-6]. The pipe vibration signal collected in this way does not need to undergo Fourier transformation, and the researcher can analyze the time sequence signals directly. However, due to the influence of noise signals and changes in operating conditions, the performance of the traditional neural network model will be greatly affected. With the development of deep learning technology, more and more technologies are applied to anomaly detection. Autoencoders (AE) are
often used for abnormal data detection [7-9]. Through the AE, the model not only obtains stable initialization weights, but also the hidden layer features of its encoding have good performance capabilities. However, relying only on the input data can easily cause the encoder to fall into overfitting and cause its generalization ability to decline, and the model will still be affected by noise signals. Subsequently, the researchers proposed denoising autoencoder (DAE) [10], that is, before the data is input to the AE, noise signals are added to the input data, so that the output of the model is less interfered by noise. However, the DAE still has the problem of discontinuous hidden space coding and some normal data might get big anomaly scores. There is still room for improvement in the generalization ability of the model.

In order to get over this problem, we utilize variation autoencoder (VAE) [11]. VAE can get contiguous hidden space and reduce the influence of the external environment on the model to a very low level. In addition, the Bayesian neural network (BNN) can get confidence coefficient for the anomaly scores. Above all, we combine the advantages of VAE and BNN and propose a Variation Bayesian neural network Autoencoder (VBAE) model for water leakage abnormal detection.

2. Modeling
Let us consider time series valuable $X \in \mathbb{R}^k$ consisting of $k$ samples in same time interval $T$. We assume that the data is generated by the contiguous unobserved latent variable $Z \in \mathbb{R}^d$. Besides, we define $W_\phi, W_\theta$ is the parameters of the Bayes neural network in encoder and decoder.

2.1. Variational Autoencoder
A VAE instance is aimed to maximize the likelihood of the given data time series. The log-likelihood of VAE can be written as:

$$
\log(p(x)) = D_{KL}(q(z | x) \parallel p(z | x)) + \mathbb{E}_{q(z|x)}[\log(p(x, z))] - \mathbb{E}_{q(z|x)}[\log q(z | x)]
$$

(1)

Note that $q(z | x)$ is the variational posterior distribution to approximate the true posterior $p(z | x)$. Consider $D_{KL}(q(z | x) \parallel p(z | x)) = 0$, so we can rewrite the equation as:

$$
\log(p(x)) \geq \mathbb{E}_{q(z|x)}[\log(p(x, z))] - \mathbb{E}_{q(z|x)}[\log q(z | x)]
$$

(2)

Then the above can be transformed to below equation by Bayes formulation:

$$
\log(p(x)) \geq \mathbb{E}_{q(z|x)}[\log(p(x | z))] - D_{KL}(q(z | x) \parallel p(z)) = L_{VAE}(\phi, \theta; x)
$$

(3)

So we need to maximize the evidence lower bound $L_{VAE}(\phi, \theta; x)$. Analysis the equation, the first item in the right side is reconstruction error, we can evaluate it by $MSE(x, \hat{x})$, where $\hat{x}$ is the output of decoder. And the second term is the regularization term. For convenience, assume $p(z) \sim \mathcal{N}(0,1)$ and in order to back-propagate gradient for the neural network, we can’t directly sample $z$ from $p(z)$ to estimate $\mathbb{E}_{q(z|x)}[\log(p(x | z))]$. The "reparameterization trick" is to move the sampling to the input layer noise variables $\epsilon_z \sim \mathcal{N}(0,1)$. Given $u_z$ and $\sigma_z$, the mean and covariance of the posterior distribution $q(z | x)$. The latent space encoder is expressed as:

$$
z = u_z + \sigma_z \odot \epsilon_z
$$

(4)

So the total loss of variational autoencoder can be rewritten as:

$$
L_{VAE}(\phi, \theta; x) = MSE(x, \hat{x}) + D_{KL}(\mathcal{N}(u_z, \sigma_z) \parallel \mathcal{N}(0,1))
$$

(5)

2.2. Bayesian neural network
In order to obtain reliable anomaly scores, we use Bayesian neural network (BNN) to encode and decode the hidden space coding $z$. Note that $W_\phi, W_\theta \sim \mathcal{N}(u_, \sigma_w)$ are the parameters of Bayesian neural network, and we define $w_i \sim \mathcal{N}(u_{wi}, \sigma_{wi})$ as the i-th parameter of the neural networks. Every
\( w_i \) is sampled by its corresponding distribution. According Bayes variational inference theory, \( \beta \) is optimized by, where \( \beta = (u_w, \sigma_w) \):

\[
\beta^* = \arg \min_{\beta} D_{KL}[q(W_\beta | \beta) \| p(w | x)]
\] (6)

Then the evidence lower bound of BNN \( L_{BNN}(\beta) \) can be written as:

\[
L_{BNN}(\beta) = \mathbb{E}_{q(\beta)}[\log p(x | f_\beta(z))] - D_{KL}[q(\beta) \| p(\beta)]
\] (7)

Observe the first term on the right side of the equation which can be integrated into \( MSE(x, \hat{x}) \) of \( L_{VAE}(\phi, \theta; x) \). Then for the second term, \( p(\beta) \) is usually taken as \( \mathcal{N}(0,1) \). And "reparameterization trick" is still used to calculate \( w_i \). \( w_i \) can be sampled by: where \( \epsilon_w \sim \mathcal{N}(0,1) \).

\[
w_i = u_w + \sigma_w \odot \epsilon_w
\] (8)

So \( L_{BNN}(\beta) \) can be rewrite as:

\[
L_{BNN}(\beta) = -D_{KL}[\mathcal{N}(u_w, \sigma_w) \| \mathcal{N}(0,1)]
\] (9)

### 2.3. Variation Bayesian neural network Autoencoder

Variation Bayesian neural network Autoencoder is shown in figure 1. Total evidence lower bound of VBAE is

\[
L_{ELBO}(\beta; x) = L_{BNN}(\beta) + L_{VAE}(\beta; x)
\] (10)

So our model can train the unsupervised time series data by maximize evidence lower bound.

#### 2.4. Model test

Variation Bayesian neural network Autoencoder is tested by anomaly scores. The output value is more different from input, the probability that the model predicts the sample value as an outlier is bigger. Anomaly scores \( SCORE \) is evaluated by reconstruction error.

\[
SCORE(x) = MSE(x, \hat{x})
\] (11)

### 3. Experiments
In this section, we collected water pipe vibration signals data set through piezoelectric acceleration sensor to evaluate the VBAE model we designed and analyze the effects of VAE and BNN on the performance of the model.

3.1. Dataset
We built the experimental platform as shown in the figure 2, and the entire signals acquisition process is as follows. Fix the sensor on the water supply pipe by a magnetic suction cup, and use the faucet to control the water release to simulate the pipe leakage. After the sensor signals are collected and processed by STM32 MCU, the values are finally sent to our server through the communication module.

![Figure 2. Water pipe vibration signal acquisition platform](image)

We collect the signal every 1s, and min max scaling was applied as preprocessing to make each value to be within 0 and 1.

\[
x' = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \tag{12}
\]

\(x\) is the collected voltage signal, \(x_{\text{max}}\) and \(x_{\text{min}}\) are the maximum and minimum values of the collected data set, and \(x'\) is the normalized value.

For the dataset, a model was trained with some value class labeled as abnormal and the other values labeled as normal.

3.2. Model setup
The implement details as explained below. The input neurons are 60. The encoder network has three fully connected layers with the activation function \(\text{relu}(x)\). The dimension of the hidden state \(z\) is 32. The decoder network has three fully connected layers with the activation function \(\text{relu}(x)\) except the last one with \(\text{sigmoid}(x)\). We divide the data set into 8:2 training set and test set, and set the batch size as 128. We choose Adam [12] as the optimizer and set learning rate as 0.1 for training 50 epochs.

The experiments are run on the PyTorch platform using an Intel Core i7-6850K, 3.60-GHz CPU, 64-GB RAM and a GeForce GTX 1080-Ti 11G GPU.
3.3. Performance evaluation

We evaluate the model through the precision rate $P$, the recall rate $R$. The precision rate $P$ is the proportion of the correct predicted in the predicted category, and the recall rate $R$ is the proportion of the correct predicted in the real category. We can calculate the precision rate $P$ and the recall rate $R$ through the confusion matrix of the classification result which is shown in the table 1.

| Real situation | Prediction result |
|----------------|-------------------|
| Positive       | $TP$              |
| Negative       | $FN$              |
| Positive       | $FP$              |
| Negative       | $TN$              |

According to the confusion matrix,

$$P = \frac{TP}{TP + FP}$$ (13)

$$R = \frac{TP}{TP + FN}$$ (14)

Precision and recall are a pair of contradictory variables. Generally, when the precision is high, the recall is often low; when the recall is high, the precision is often low. We need to consider these two values at the same time to evaluate the model and $F1$ score can achieve this. We can get the $F1$ score from equation (15).

$$F1 = \frac{2 \times P \times R}{P + R} = \frac{2 \times TP}{n + TP + TN}$$ (15)

$n$ is the total number of samples. The larger the value of $F1$, the better the performance of the model.

There are 60 sample values as the input $x$ each time, which is the data collected in 1 minute and the output 60 values $x$ are in $[0,1]$. The larger the $SCORE$, the greater the probability of water leakage in this minute. We input test data and sort the abnormally scores $SCORE$ from largest to smallest. We select the top 5, top 10, and top 20 largest abnormally scores from the one batch data, and calculate $P, R$ and $F1$ score to evaluate the VBAE model. Simultaneously, we compare VBAE with SVM and AE models.

| Model   | precision | recall | $F1$ score |
|---------|-----------|--------|------------|
| SVM     | 5         | 0.912  | 0.206      | 0.336      |
|         | 10        | 0.873  | 0.422      | 0.569      |
|         | 20        | 0.569  | 0.903      | 0.698      |
| AE      | 5         | 0.908  | 0.215      | 0.348      |
|         | 10        | 0.880  | 0.435      | 0.582      |
|         | 20        | 0.835  | 0.921      | 0.876      |
| VBAE    | 5         | 0.939  | 0.239      | 0.381      |
|         | 10        | 0.923  | 0.476      | 0.628      |
|         | 20        | 0.869  | 0.959      | 0.912      |

3.4. Ablation study

To verify the effectiveness of VAE and BNN, here we show a comparison between the full VBAE model and its two ablation models: 1) BNN; and 2) VAE
Table 3. The comparison of BNN, VAE and VBAE.

| Model | precision | recall | f1 score |
|-------|-----------|--------|----------|
| BNN   |           |        |          |
| 5     | 0.912     | 0.217  | 0.350    |
| 10    | 0.901     | 0.457  | 0.606    |
| 20    | 0.846     | 0.939  | 0.890    |
| VAE   |           |        |          |
| 5     | 0.925     | 0.221  | 0.357    |
| 10    | 0.911     | 0.459  | 0.610    |
| 20    | 0.860     | 0.946  | 0.901    |
| VBAE  |           |        |          |
| 5     | 0.939     | 0.239  | 0.381    |
| 10    | 0.923     | 0.476  | 0.628    |
| 20    | 0.869     | 0.959  | 0.912    |

4. Conclusion
In this paper, we combined the VAE and BNN models, and proposed the VBAE model for water pipe leakage detection. Compared with other models, the VBAE model has higher performance in the application of water leakage detection. In addition, Ablation study proved that both BNN and VAE play an important role in the robustness of the model.

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