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FM Broadcasting Monitoring Method Based on Time Series Analysis

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Abstract

With the development of modern wireless applications and the popularization of Artificial Intelligence (AI), the intelligentization of radio monitoring system is a development direction. In this context, in order to achieve an intelligent FM broadcasting monitoring, this paper implemented an algorithm which consists three steps. Firstly, occupied channel is searched based on energy detection. Then, Autoregressive Integrated Moving Average (ARIMA) model is adopted to predict the abnormality in the spectrum of FM broadcast. Thirdly, a completely-fully connected neural network is applied to classify the spectrum, to find whether it is authorized spectrum or the frequency bands are occupied by unauthorized users. Results show that the recognition rate for authorized and unauthorized user is 100% and 79%, respectively.

1 Introduction

With the successful application of artificial intelligence in various fields, such as face recognition and natural speech processing. How to integrate artificial intelligence into modern radio monitoring system has become a research hotspot[1-4]. Yang et al.[5] proposed a novel method to monitor FM broadcast based on acoustic feature recognition. Žunić et al. [6] described an efficient technique for finding different types of anomalies in GPS data, and the algorithm is implemented and used as a part of the GPS tracking system that is used by distribution companies in Bosnia and Herzegovina. Lee et al. [7] proposed a feature image-based Automatic Modulation Classification (AMC) method to classify modulation type of communication signals, with which various features were transformed in a two-dimensional image and this image is used as the input of the Convolutional Neural Network (CNN). Results show that the CNN based method improves classification performance. Balint et al. [8] presented a Markov chain model for time domain spectrum occupancy. The results show that Markov chains can accurate model the statistical properties of spectrum occupancy in high frequency domain. Rajendran et al. [9] presented an adversarial autoencoder based anomaly detector for wireless spectrum anomaly detection using power spectral density data. It is demonstrated that the model achieves an average anomaly detection accuracy above 80% at a constant false alarm rate of 1% along with anomaly localization in an unsupervised setting. Ozyegen et al. [10] investigated the AI models such as LSTM, recurrent ANNs, ARIMA and TDNN for predicting spectrum occupancy in multiple time horizons in Land Mobile Radio bands. The computational complexity of these models are compared. Results show that LSTM networks that remember long term dependencies and designed to work with time series provide an improvement accurately predicting spectrum occupancy in LMR bands. Roy et al. [11] proposed the radio frequency adversarial learning framework for building a robust system to identify rogue RF transmitters by designing and implementing a Generative Adversarial Net (GAN). A discriminator model was implemented and a 99.9% accuracy for discriminates between the rusted transmitters and the counterfeit ones had been achieved.

In this paper, the architecture of an intelligent FM broadcasting monitoring system which mainly consists of spectrum sensing nodes and a back-end server is proposed. An algorithm is implemented for anomalous spectrum detection. It consists three steps: the occupied channel is searched, anomalous spectrum prediction based on ARIMA and spectrum classification using a completely-fully connected neural network. Experiment results show that the recognition rate is 100% for authorized user, and 79% for unauthorized user. The proposed method may have potential application in modern radio monitoring.

2 Architecture of the Monitoring System

As shown in Figure 1, the monitoring system is mainly composed of spectrum sensing nodes and back-end servers. The hardware used in the design of the spectrum sensing

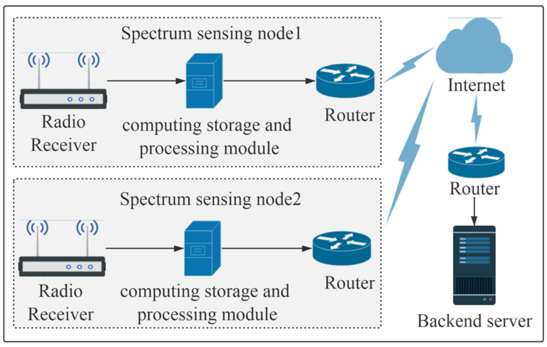

Figure 1 Architecture of the monitoring system.

node includes the embedded industrial computer, 14 bit SDR receiver and FM antenna. It is mainly responsible for receiving and saving the FM broadcasting spectrum data, analyzing and processing the data, detecting the authorized and unauthorized FM broadcast stations, and sending the detection results to the back-end server.

3 Method and Experiment Results

The flowchart of the FM broadcast monitoring system is shown in Figure 2. The detection algorithm consists of three main steps. Firstly, searching the occupied FM channel in the range of 87-108MHz through energy detection and get the raw data of power spectrum variation over time. Then, making time series prediction using the raw spectrum data. When the difference between the predicted value and the actual value is detected, it is considered as an abnormality. Finally, the anomalous spectrum predicted by time series model ARIMA is further confirmed by spectrum image classification using completely-fully connected neural network, and the result is sent to the back-end server.

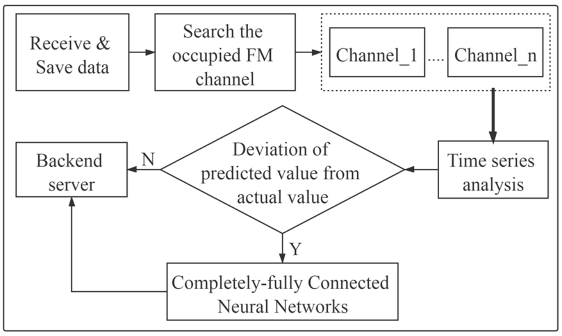

Figure 2. The flowchart of the FM broadcast monitoring system.

3.1 Searching the occupied FM channel

The FM frequency band is divided into 210 channels of which the bandwidth is 120kHz. The average energy of each channel is calculated and compared with the floor noise using:

$$\frac{1}{N}\sum_{i=1}^{N} P_i > P_0, \tag{1}$$

where N is the total number of sample point in each channel, P_i is the received power at each frequency, P_0 is the power of floor noise. When the average energy is greater than the noise floor, the channel is considered as occupied and the spectrum data is recorded. Here, we set P_0 = -93dBm, and obtained a total of 19 occupied FM channel, as shown in Figure 3.

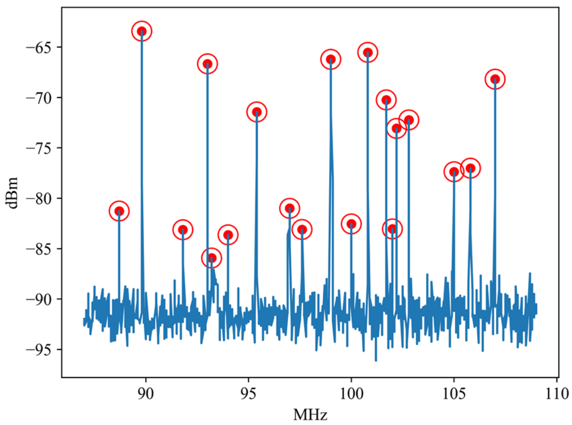

Figure 3. Searching the occupied FM channel

3.2 Time series prediction

We collected the spectrum data of FM broadcasting band from 22 Dec, 2019 to 26 Dec, 2019, at HuaiZhou Building of Donglu Campus, Yunnan University, China. Taking the FM channel of 107.1MHz as an example, the relationship between received power and time is shown in Figure 4. It is clear that this is a periodic time series. The value fluctuates up and down in a regular day cycle. FM broadcast continues to play in the daytime and is closed in the early morning.

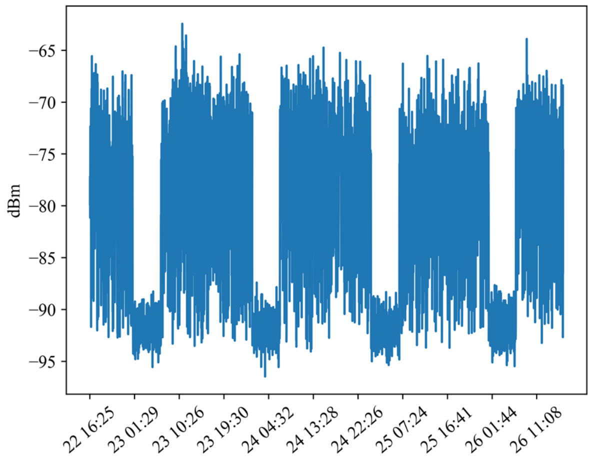

Figure 4. Time series data of four days for the FM channel 107.1MHz.

ARIMA model is used to analyze the time series data. ARIMA (p, d, q) model can be expressed as [12]

$$\Phi_p(B)(1-B)^d X_t = \theta_0 + \Theta_q(B) a_t, \tag{2}$$

where $\Phi_p(B) = 1-\phi_1 B - \cdots - \phi_p B^p$, $\Theta_q(B) = 1-\theta_1 B - \cdots - \theta_q B^q$, ϕ_m represents the m-th AR coefficient, θ_n the nth MA coefficient, X_t average energy of predicted channel, a_t the error, and B backward shift operator. In this paper, Autocorrelation function (ACF) and Partial autocorrelation coefficient (PACF) are used to estimate p and q parameters of ARIMA (p, d, q). When ACF crosses the confidence interval for the first time, p value is the horizontal axis value. When PACF crosses the confidence interval for the first time, q value is the horizontal axis value. As shown in Figure 5, we can get p = 1, q = 1. ARIMA (1,1,1) was used in this work.

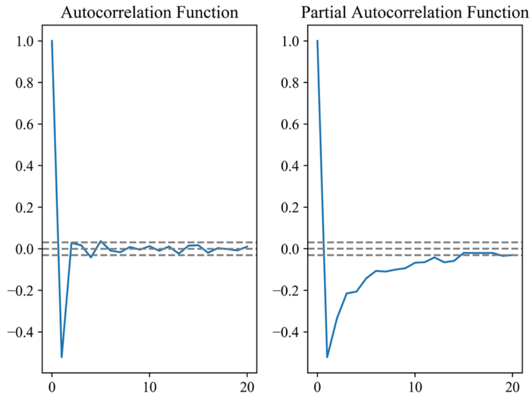

Figure 5. Estimating p and q parameters of ARIMA (p, d, q) by ACF and PACF.

For the ARIMA (1,1,1), the data must be stable sequences, it is very important to check the stability of time series data. Data is considered stable if the mean and variance are constant functions in time. For Dickey-Fuller test, if the test statistic is less than the critical value, the data is stable; otherwise, it is unstable. Table 1 shows that the data is stable at confidence level of 95%.

Table 1. Result of Dickey-Fuller test

Test Statistic	Critical value(1%)	Critical value(5%)	Critical value(10%)
-2.97	-3.43	-2.86	-2.57

Figure 6 shows a comparison of the predicted spectrum (the green line) and actual spectrum (red line) of the fourth day. The predicted spectrum reveal that the frequency band is free at 1am on January 26, while the actual spectrum show that the frequency band is occupied. As a consequence, the appearance of an abnormal spectrum is predicted.

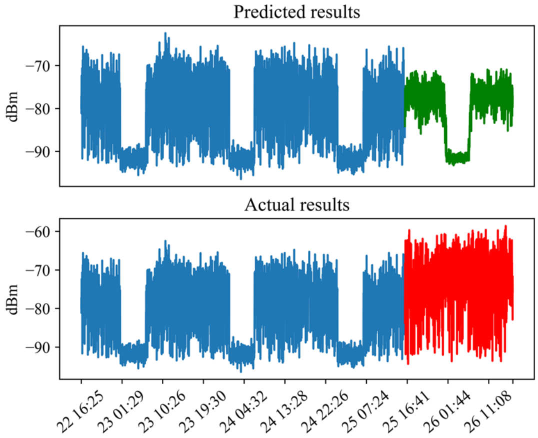

Figure 6. A comparation between predicted value and actual value.

3.3 Spectrum data classification

When the anomalous is found, the system call the trained completely-fully connected neural network to classify whether it is authorized spectrum or the frequency channels are occupied by unauthorized users. The network consists of three layers as shown in Figure 7. The optimization function is Stochastic Gradient Descent (SGD). The resulting confusion matrix is shown in Figure 8. The recognition rate of authorized spectrum user is 100%, and the unauthorized recognition rate is 79%. This is mainly due to the fact that the dynamic range of the spectrum data is large and the random fluctuation is obvious. Figure 9 shows several samples of the authorized and unauthorized spectrum.

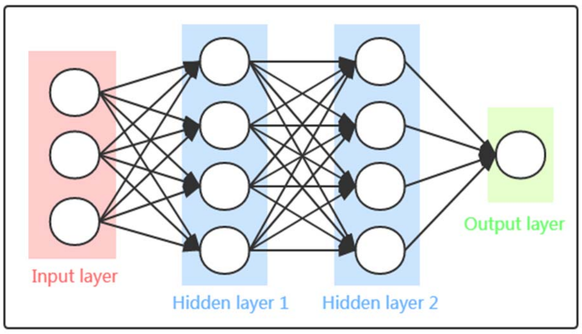

Figure 7. Completely-fully connected neural network.

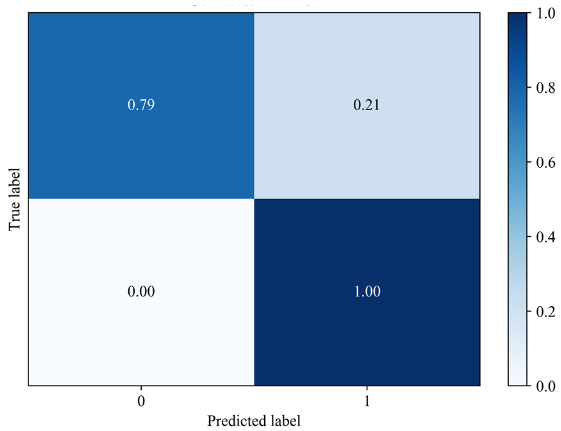

Figure 8. Confusion matrix.

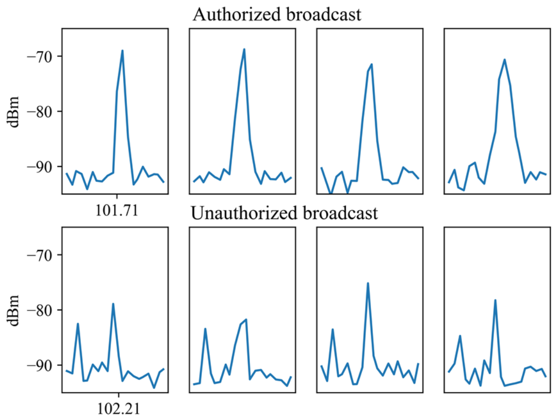

Figure 9. Authorized broadcast signal and unauthorized broadcast signal.

4 Conclusions

In this paper, an architecture of the FM broadcasting monitoring system is proposed. An algorithm consisted of the occupied channel detection, time series prediction and completely-fully connected neural network classification is implemented. This is a step towards the intelligentization of radio monitoring systems. In the next stage, we will optimize the node and back-end server software and deploy this system in Donglu Campus of Yunnan University.

5 Acknowledgements

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6 References

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