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Supplementary materials for

Xiang LI, Yibing LI, Chunrui TANG, Yingsong LI, 2022. Modulation recognition network of multi-scale analysis with deep threshold noise elimination.

1 Modulation classification methods

The modulation classification methods are divided into manual and automatic modulation classification techniques. The manual modulation technique relies on the down-conversion of the received high-frequency signal to determine the type of signal modulation through an oscilloscope, spectrum analyzer, demodulator, etc. Manual classification recognizes limited types and high complexity. Compared to the complex manual modulation recognition, machines automatically do the existing modulation recognition methods (Wang et al., 2019).

2 The architecture of the signal transceiver system

Send the read data source through the TX channel in the UHD USRP sink. USRP is a flexible and powerful general-purpose software radio peripheral. The low cost of wide broadband makes USRP a cost-effective advantage (Zitouni and George, 2016). During the transmission process, the signal processing inside the USRP is divided into two stages. In the first stage, the high-speed digital signal processing FPGA in the motherboard converts the digital baseband signal in the computer into a digital intermediate frequency signal. After sending control and digital up-conversion, the signal is converted into data in the analog domain through the DAC module. In the second stage, the child board filters the IF signal in the analog domain to smooth the signal and then multiplies it with the crystal oscillator signal to obtain the RF signal. The signal radiated by the antenna is transmitted through the radio environment. Then the signal is received through the RX channel. The child board's low noise amplifier and crystal oscillator down convert the signal from RF to IF and perform filtering and smoothing to prevent aliasing. After that, the ADC in the motherboard performs the analog-to-digital conversion and sends it to the FPGA for digital down-conversion and receiving control. GNU radio completes the communication establishment with USRP by calling the API interface provided by the UHD driver (Liu et al., 2017). The QT GUI time sink module in GNU radio is responsible for representing the signal. After giving a complex number to the input module, the module outputs both the real part and imaginary part of the signal, and it can be judged whether the transmission and reception are completed through the signal figure. The in-phase and quadrature components of the signal acquisition are transferred to the computer through the file sink module and saved as a file of the corresponding modulation type. The highly compatible integration of software and hardware platforms facilitates complex signal processing.

3 The layer in the signal recognition system framework

This network introduces BN to solve the gradient explosion and disappearance caused by reverse gradient

propagation. Besides, the data distribution after the action of the BN tends to be stable so that the subsequent network layers can learn features based on appropriate data distribution and accelerate the convergence speed of the loss function. We select the LeakyRelu activation function to enhance the nonlinearity of the network. Additionally, when LeakyReLu takes a negative value, it has a slight slope to solve the problem of the input data neurons stopping learning. The network introduces the dropout mechanism to increase the sparsity and randomness of the network design and avoid spending more time learning unimportant features.

4 Autoencoder

As one of the mainstream architectures in deep learning, the purpose of the autoencoder is to minimize the error so that the output reconstructs the input (Bengio et al., 2013). However, the basic autoencoder learns only with a single hidden layer, which is easy to get a linear mapping result. Researchers proposed a deep autoencoder, setting multiple hidden layers and training the network by backpropagation to solve the problem of a single hidden layer autoencoder simply copying the input as output (Hinton and Salakhutdinov, 2006). The deep autoencoder can efficiently learn the hidden layer representation of the input data to get more objective and complete features. The algorithm model contains the encoder, and the decoder. The function of the encoder is to encode the input data $\boldsymbol{x}$ as a latent variable $\boldsymbol{h}$ by feature extraction and capture the most significant features of the neural network through this behavior. The decoder converts the extracted features into $\boldsymbol{x}^R$ through the decoding operation, restoring the features to the original dimension.

5 Deep residual network

The network learns more sophisticated features with deeper network layers, and the training learns better system recognition. However, when the depth is too deep, the network will face the phenomenon of degradation, which means that the performance rapidly reaches saturation or even decreases. Assuming that the model at layer m has been trained to the optimal network at layer n (where $m > n$), the network at layers $m-n$ is redundant. Due to a nonlinear activation function, the redundant network action of $m-n$ layers generates irreversible information loss and makes the network degenerate. Kai-Ming He proposed the concept of the deep residual network in his article (He et al., 2016) to reduce the effect of redundant layers on network degradation. It divides the network into two parallel parts. One keeps the original network design. The other is designed as a bypass connection, which is an identity mapping corresponding to the starting layer of the original network, and the mapping is added across multiple hidden layers to the output layer of the original network. The two-act together as the input to the next layer. In the deep residual network, $\boldsymbol{x}$ is the input, $F(\boldsymbol{x})$ is the output after the action of the original network, and let the final output of the network be $H(\boldsymbol{x})$, then $H(\boldsymbol{x}) = F(\boldsymbol{x}) + \boldsymbol{x}$. They are assuming that $F(\boldsymbol{x})$ acts on a redundant layer, which means it lacks a positive effect on the output, then $H(\boldsymbol{x})$, in the presence of $\boldsymbol{x}$, can guarantee that the output results are at least consistent with those acting directly on $\boldsymbol{x}$, namely $H(\boldsymbol{x}) \approx \boldsymbol{x}$. Calling $F(\boldsymbol{x}) = H(\boldsymbol{x}) - \boldsymbol{x}$ the residual term, then $F(\boldsymbol{x}) \approx 0$. Since parameter initialization is generally around zero, learning $F(\boldsymbol{x}) \approx 0$ is simpler than directly learning $H(\boldsymbol{x}) \approx \boldsymbol{x}$ when parameters are updated. Moreover, the residual model can improve the gradient disappearance that occurs when the gradient is backpropagated. In backpropagation, ε represents the loss equation, which is obtained by the chain rule:

$$\frac{\partial \varepsilon}{\partial \boldsymbol{x}} = \frac{\partial \varepsilon}{\partial H(\boldsymbol{x})} \cdot \frac{\partial H(\boldsymbol{x})}{\partial \boldsymbol{x}} = \frac{\partial \varepsilon}{\partial H(\boldsymbol{x})} \left[1 + \frac{\partial F(\boldsymbol{x})}{\partial \boldsymbol{x}} \right]. \tag{S1}$$

Even if $\frac{\partial F(\boldsymbol{x})}{\partial \boldsymbol{x}} = 0$, the lossless propagation term still exists in the gradient, with no phenomenon of gradient disappearance.

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