Prototype of Data Link Based on Random Modulation Hopping and Automatic Modulation Recognition

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Abstract. A model of data link system based on modulation hopping and Automatic Modulation Recognition (AMR) is proposed, and the prototype of the proposed system is developed with GNU radio platform and the universal software radio peripheral (USRP). At the transmitting end of the prototype, the random sequence is generated to control modulation hopping pattern. At the receiver part, an AMR Network module recognizes the modulation mode and sends the information to the demodulation module to obtain the data flow. In the experiment, the speed of modulation recognition and the tracking ability of the modulation hopping under typical working environments are verified and analysed. The experimental results and the analysis of the corresponding parameters verify the rationality and availability of the system design.

1. Introduction
To further improve the anti-interception ability of data link, the modulation hopping is proposed [1-4]. At the early stage, Gao [1] applied for a patent about modulation hopping technology for the frequency hopping communication. Then, Tai did research on synchronization scheme of modulation hopping system [2] and designed a wide-gap chaos modulation hopping pattern based on time of date (TOD). Feng [3] proposed a secure communication system model based on pseudo-random sequence hopping. Recently, Ma [4] proposed communication technique based on information entropy and chaotic coding for modulation encryption. When the modulation hopping is combined with frequency-hopping, it truly more difficult to crack the communication system. However, because the hopping pattern of the transmitter is pre-designed, once the hopping pattern is cracked, it can be easily de-hopped. After the carrier frequency synchronization and symbol rate synchronization, the modulation mode can be estimated by Automatic Modulation Recognition (AMR) technology [5], and then the information transmitted is intercepted.

In the past few years, deep learning (DL) method have greatly increased the capacity for feature extraction and learning [6]. The earliest work which applies the DL method to AMR problem is proposed by O‘Shea et al. [7], who treat the in-phase component (I) and quadrature (Q) channel of the receive signals as the input of the Convolutional Neural Network (CNN). However, the AMR network simply composed of CNN can only process signal sequences of fixed length, limiting the application of the model. To solve the problem above, O‘Shea [8] combine the CNN with Long Short-Term Memory (LSTM) [9] to improve the performance of the original classifier. In the following studies, Rajendran et al. [10] proposed a modulation recognition network containing only LSTM units to adapt to the variable length communication signal sequence. The authors’ team also proposed an AMR model composed of CNN and LSTM which is verified by a UAV data link signal database [11]. In terms of the different network structures, in Ref. [12] proposed two AMC models based on Res-Net and Dense-Net respectively, and in
Ref. [13] proposed to use one-dimensional CNN to improve the existing deep neural network structure, as well as verify the impact of carrier offset, symbol rate, multi-path fading and other factors on the performance of AMR network.

2. System Model

Figure 1 shows simplified system model based on modulation hopping and AMR network.

As shown in figure 1, at the transmitter part, the Random Sequence Generator module generates random sequence to control modulation hopping pattern. Corroding to random hopping pattern, the modulation election controller output the modulation mode information to select the corresponding Modulation Generator module. The data produced by the Data Flow Generator is input to the modulation module and transmitted through the USRP (Universal Software Radio Peripheral). At the receiver part, after the carrier synchronization and code synchronization supported by the Synchronization System. The AMR (Automatic Modulation Recognition) Network module recognizes the modulation mode and gives it to the Demodulation module to obtain the data flow.

3. AMR Network Based on CNN and LSTM

Figure 2 shows the proposed modulation recognition network and its training process.

As shown in figure 2, the proposed AMR network consists of a one-dimension CNN and a LSTM network. Different from the general machine learning model, an extra step of data segmentation is
 introduced in the system. The Nadam optimization algorithm is used to train the model. Table 1 shows the configurations of the proposed modulation recognition network.

| Name                              | Configuration                                      |
|-----------------------------------|----------------------------------------------------|
| One-dimension CNN network         | Convolution × 3 \(a*1, b*1\) and \(c*1\).         |
| LSTM network                      | LSTM × 3 \((L+a+b+c-3)\)                          |
| Full connected layer              | 11 classes                                         |

3.1. One-Dimension CNN Network
The convolution kernel size of convolution layer 1, 2, 3 is set to \(a*1, b*1\) and \(c*1\). Take the input signal fragment \(X_i = \{s_i, s_i, \ldots, s_i\}\) as an example, the input signal sequence is calculated according to the following equation:

\[
h^k_i = f_a((W^k_i * x_i) + b^k_i)
\]

where \(x_i\) is the \(i\)th segmented data, \(h^k_i\) is the output of the \(k\)th layer, \(f_a\) is the activation function, such as the \(\tanh\) or \(\text{sigmoid}\) function, \(W^k_i\) is the weight parameter on the \(k\)th layer, \(b^k_i\) is the bias. The final feature sequence output by the three-layer CNN network is:

\[
C_1 = \{c_1, c_1, \ldots, c_{L(a+b+c)}\}
\]

3.2. LSTM Network
The feature sequence (2) of CNN network is input into LSTM network, which is composed of \((L+a+b+c-3)\) isomorphic LSTM cells, each cell unit is connected in time sequence. The output feature sequence output by the LSTM network is expressed as:

\[
L_i = \{l_i, l_i, \ldots, l_{L(a+b+c)}\}
\]

The element in equation (3) is expressed as:

\[
l_j = f_{lstm}(c_j, h_{j+1}, C_{j+1})
\]

where \(f_{lstm}\) is the forward computing function of the LSTM cell, \(c_j, h_{j+1}, C_{j+1}\) are three parameters in the function which denote the input of the current cell, the output of the former cell and the state of the former cell.

3.3. Feature Fusion by Full Connected Network
For each segment \(X_i(1 \leq i \leq L)\), a feature sequence \(L_i(1 \leq i \leq L)\) is output through CNN and LSTM network. These feature sequences are arranged in chronological order, and a vector \(f\) with dimension \([L^*L+(a+b+c-3),1]\) is obtained. Two cascaded full-connection layers are chosen to form a full-connection network, and the final output matrix is \(N\) modulation modes.

For the classification problem, the output often needs to be processed by exponential probability. The formula of the exponential probability model can be defined as equation (5):
\[ p_y = \sum_s e^{w_s^T x + b_s} \]
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where \( x \) is the feature input, \( y \) is the label, \( z \) is the exponential probability value.

For training set \( \{(x^{(i)}, y^{(i)})\}_{i=1}^m \), \( y^i \in \{1, 2, 3, \ldots, k\} \), there are \( k \) class of modulation mode. For every input \( x \), the probability \( p(y = j | x) \) for each class is defined as follow:

\[
h_y(x') = \begin{bmatrix}
p(y' = 1 | x'; \theta) \\
p(y' = 2 | x'; \theta) \\
\vdots \\
p(y' = k | x'; \theta)
\end{bmatrix} = \frac{1}{\sum_{j=1}^k e^{\theta^T x'}}
\]

The cost function can be defined as Minimizing the negative logarithmic likelihood functions, as shown in equation (7):

\[
J(\theta) = -\frac{1}{m} \sum_{i=1}^m \sum_{j=1}^k \{1(y = j) \cdot \log p(y = j | x'; \theta) \}
\]

The function \( 1\{j = y^{(i)}\} \) denotes that if the \( i \) th sample is belong to class \( j \), then \( y^{(i)} = j \).

4. Experiment Results

4.1. Configuration for the Prototype

We construct the prototype of the emitter and receiver with GNU radio [14] and the universal software radio peripheral (USRP) B210 software defined radio (SDR) and implement an over-the-air (OTA) test bed. Figure 3 shows the configuration for over-the-air transmission of signals. The carrier frequency is set to 2100MHz, and the symbol rate is set to 19200bps.

4.2. Configuration for the Prototype

4.2.1. Speed of Modulation Recognition. The training loss of model under different SNR conditions are tested. The training parameters are as follows: the length of the split window is 400, the step of the training step is 10000, and the initial learning rate is 0.005. Figure 4 shows the trend of learning loss with the number of training iterations under SNR=5dB.
Figure 4. Learning loss with the number of training iterations under SNR=5dB.

It can be seen in figure 4 that the recognition model takes about 2000 iterations to converge. For high performance computing platforms, this makes prototype system real-time possible.

4.2.2. System-Level Verification. In system-level verification part, the tracking performance of the modulation recognition model is verified when the modulation model is hopping. The hopping frequency is set to 10Hz and 100Hz, respectively. Figure 5 shows the tracking performance of the system under different hopping frequency.

Figure 5. Tracking performance of the system under different hopping frequency.
As shown in figure 5, under the hopping frequency of 10Hz and 100Hz, the system can to achieve good tracking accuracy and the delay remains on the order of microseconds. If the computational performance of the experimental platform can be further improved, the delay can be further reduced, and a higher hopping frequency are supported.

5. Conclusions
A prototype of data link based on modulation hopping and Automatic Modulation Recognition (AMR) is developed in this paper. The transmitting end can support modulation hopping in a purely random or pseudo-random manner, and the AMR module based on CNN and LSTM is constructed in the receiver to identify the corresponding hopping modulation model. At the experimental part, the test-bed based on GNU radio and the universal software radio peripheral (USRP) is used to exam the performance of the prototype system. The speed of modulation recognition and the tracking ability of the modulation hopping of the receiver are verified and analysed.

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