Open Set Modulation Recognition Based on Dual-Channel LSTM Model

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Abstract—Deep neural networks have achieved great success in computer vision, speech recognition and many other areas. The potential of recurrent neural networks especially the Long Short-Term Memory (LSTM) for open set communication signal modulation recognition is investigated in this letter. Time-domain sampled signals are first converted to two normalized matrices which will be fed into a four layer Dual-Channel LSTM network tailored for open set modulation recognition. With two cascaded Dual-Channel LSTM layers, the designed network can automatically learn sequence-correlated features from the raw data. With center loss and weibull distribution, proposed algorithm can recognize partial open set modulations. Experiments on the public RadioML dataset indicates that different analog and digital modulations can be effectively classified by the proposed model, while partial open set modulations can be recognized. Quantitative analysis on the dataset shows that the proposed method can achieve an average accuracy of 90.2% at varying SNR ranging from 0dB to 18dB in classifying the considered 11 classes, while accuracy of open set experiment dramatically improved by 14.2%.

Index Terms—Deep learning, DC-LSTM, LSTM, modulation recognition, open set.

I. INTRODUCTION

The recognition of modulation signals plays an important role in cognitive radio and spectrum monitoring owing to the rich information contained in communication signals. Numerous automatic modulation recognition algorithms have been proposed which mainly include decision theory based methods and machine learning based methods [1].

The letter only focuses on machine learning based algorithms due to the huge demand of parameters estimation of decision theory based algorithms. Current machine learning based algorithms can be divided into two types: methods based on traditional machine learning and methods based on deep learning. Traditional machine learning based modulation recognition algorithms need to design handcrafted expert features extractor and combine features with machine learning algorithms appropriately. Deep learning has achieved great success in computer vision and many other areas [2]. They have also been applied to modulation recognition. Researchers have utilized deep neural network to improve the performance of classifiers [3], to recognize modulations by constellation diagram [4], by feature graph [5], [6] or by sampling signals [7]–[9].

Nevertheless, much works so far just only focused on modulation classification of close set, hence open set unknown classes cannot be rejected. Not only the deep neural networks can be used to extract features automatically from modulation signals, they can also be used to recognize open set signals. Open set deep neural network based on weibull distribution is proposed in [10] to recognize images of unknown classes, however the activation vectors of which are separable instead of discriminative. The Dual-Channel LSTM network (DC-LSTM) which achieves state of the art classification performance is firstly introduced, then DC-LSTM will be combined with center loss [11] and weibull distribution [10] to realize open set modulation recognition.

The proposed scheme consists of the following steps: 1) convert the complex communication modulation signal to two matrices which are appropriate as a recurrent neural network input; 2) two cascaded Dual-Channel long short-term memory layers designed to extract sequence-correlated features of In-phase/Quadrature signal components and Amplitude/Phase signal components; 3) two fully connected layers designed to concatenate features and classify features to corresponding classes; 4) an extreme value distribution - weibull distribution adopted to fit the cut off probability of the distance from features to features centers and modify neural network outputs. The effectiveness of the methodology is validated on a standard public dataset RadioML2016.10a [12]. Quantitative analysis indicated that the proposed method can achieve the state of the art performance and recognize open set modulations. It is the first effort to achieve open set modulation recognition to our best knowledge.

II. METHODOLOGY

A. Two Real Matrices Representation for Modulation Signal

The general representation of the received signal can be fully expressed as a complex vector which is given by:

\[ r(n) = s(n) + c(n) + N(n) \]  

(1)

where \( s(n) \) is the emitting noise free complex baseband envelop of the received signal \( r(n) \), \( N(n) \) is Additive White Gaussian Noise (AWGN) with zero mean and variance \( \sigma_n^2 \) and \( c(n) \) is the time varying impulse response of wireless transmission channel [9]. It has to be converted to real matrices in order to be able to be fed into real-valued recurrent neural networks. Two matrices representation \( V_1, V_2 \) tailored for neural networks are proposed as follows:

\[ R = \sqrt{\frac{1}{T} \sum_{n=1}^{T} |r(n)|^2} \]  

(2)
C. Loss Function

The loss function of proposed network is different from traditional classification neural networks whose loss function only contains cross-entropy (also named Softmax Loss). A loss function which combines cross-entropy with center loss is introduced in [11], with which minimal classification error and clustering features can be obtained simultaneously. It can be written as:

\[
L = L_s + \lambda L_c = - \sum_{i=1}^{m} \log \frac{e^{W_y^T x_i + b_y}}{\sum_{j=1}^{m} e^{W_y^T x_j + b_y}} + \frac{\lambda}{2} \sum_{i=1}^{m} \|x_i - c_{y_i}\|_2^2
\]

where \(x_i\) represents the \(i_{th}\) output of the penultimate layer, \(L_s\) and \(L_c\) represent cross-entropy and center loss respectively, \(c_{y_i}\) represents the center vector whose label equal to \(y_i\), \(\lambda\) is the control parameter which balances cross-entropy and center loss.

D. Training and Open Set Testing

Parameters needed to be updated of proposed model contain parameters of network architecture and classes centers. Parameters of network architecture are updated by Adam gradient descent algorithm with mini-batch size 256 and fixed learning rate 0.01. Centers are updated iteratively each mini-batch with initial centers equal to zero, \(\lambda\) is set to 0.1 and \(\alpha\) is set to 0.5, detailed process can be found in [11]. Xaiver initial method is adopted to maintain the performance. All models are running on one workstation who has 128GB memory, K40c GPU and Xeon ES-2640 CPU with deep learning library Keras and Tensorflow.

The special extreme value distribution - weibull distribution is adopted to fit the probability distribution of the distance from features to feature centers after classification model and feature centers acquired. The number \(M\) (which is determined by experience) is decided to choose how many farthest examples to fit the probability distribution function which is expressed as follows:

\[
f(x|a, b) = \frac{b}{a} \left(\frac{x}{a}\right)^{b-1} e^{-\left(\frac{x}{a}\right)^b} I_{(0,\infty)}(x)
\]

where \(a\) and \(b\) control the scale and shape of the distribution, \(I\) represents indicative function. Hence the cumulative distribution function can be written as:

\[
F(x|a, b) = 1 - e^{-\left(\frac{x}{a}\right)^b} I_{(0,\infty)}(x)
\]

the inverse cumulative distribution function is used to evaluate the probability of \(x\) bigger than a value:

\[
InvF(x|a, b) = 1 - F(x|a, b) = e^{-\left(\frac{x}{a}\right)^b} I_{(0,\infty)}(x)
\]

the predictions can be modified by \(a_i,b_i\) which are calculated from features \(v^{(l-1)}\) and the corresponding centers \(c_i\) as follows:

\[
\hat{v}^{(l)}(i) = \begin{cases} 
   InvF \left(\|v^{(l-1)}_i - c_i\|^2|a_i, b_i\right) & v^{(l)}(i) > 0 \\
   v^{(l)}(i) & v^{(l)}(i) < 0
\end{cases}
\]
than information in Amplitude and Phase. Besides, it is hard
time and classification performance. The results also indicate
following experiment considering parameters number, training
LSTM achieves 2.2% improvement than LSTM-AP model
IQ and AP information combined, the performance of DC-
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different from the results of [9] where IQ information cannot
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treated in Tabel. II, it can be concluded that whether utilizing
ranging from 0dB to 18dB. From the simulation results illus-
A. Close Set Experiment
Four LSTM based architectures - LSTM with IQ (LSTM-IQ),
LSTM with AP (LSTM-AP), DC-LSTM, and DC-Bidirectional-LSTM (DC-BLSTM) are compared to choose the
appropriate model. These models have been trained and
tested on RadioML dataset and the training process is similar to [9]. Parameters of different architectures, parameters
number, and training time are listed in Table II.

After training 70 epochs on the dataset, DC-LSTM model
can achieve an average accuracy of 90.2% at varying SNR
ranging from 0dB to 18dB. From the simulation results illustrated in Tabel. II it can be concluded that whether utilizing
IQ information or AP information, LSTM based model could
achieve high recognition performance. This is significantly
different from the results of [9] where IQ information cannot
be used to recognize modulations, it is mainly caused by the
truth that IQ information is not normalized. In addition, with
IQ and AP information combined, the performance of DC-
LSTM achieves 2.2% improvement than LSTM-AP model
which has achieved the state of the art performance. DC-
LSTM model is chosen as the network architecture for the
following experiment considering parameters number, training
time and classification performance. The results also indicate
that information in In-phase and Quadrature is more important
than information in Amplitude and Phase. Besides, it is hard
to declare which model is best among LSTM-IQ, DC-LSTM
and DC-BLSTM.

B. Open Set Experiment
To evaluate the open set recognition performance of
the proposed model, the RadioML dataset is splitted into
two subsets - training set and testing set where training
set only contains partial types while testing set contains all
types. Network weights and feature centers are acquired from
training on the training set and weibull distribution parameters
are calculated from centers and feature distribution. M is set
to 1000 according to simulation experiments.

Softmax loss only based model, softmax loss based
model with weibull distribution fitting and center loss based
model with weibull distribution fitting for open set recognition
are shorted as SL-O,SL-WF and CL-WF for convenience.
Comparison of different open set scene is illustrated in Fig
2 where a vs b indicates that there are a classes in training
set and b classes in testing set respectively. Test on the testing
dataset reveals that proposed CL-WF model could achieve a
significant improvement of 14.2% than SL-O model. It should
be noticed that error classified example in SL-O model which
are ultimately modified by CL-WF model to unknown
class would be treated as rightly classified. From Fig 2 we
can also see that proposed algorithm could recognize partial open
set modulation types even the model has never seen before.
Besides CL-WF model distinctly performs better than SL-WF
model [10]. The essential reason is that features in this model
are not only separable but also discriminative.

From section above we have seen that SL-WF model
cannot tackle the recognition task when encountering unknown

III. EXPERIMENTS

To evaluate the proposed framework, a standard public
modulation signal dataset RadioML is considered, detailed
parameters is shown in Table I. Two experiments - close set
experiment and open set experiment are considered, where
the training and testing set include all types in close set experiment
and only testing set includes all types in open set experiment.
These two experiments are used to evaluate the close set
recognition performance and open set recognition performance
respectively.

A. Close Set Experiment

Table I shows the parameter setting for experiments.

| Modulations              | Samples per symbol | Sample length | SNR Range       | Number of training samples | Number of testing samples |
|-------------------------|--------------------|---------------|-----------------|---------------------------|--------------------------|
| 8PSK,AM-DSB,AM-SSB,BPSK,CPFSK,GFSK,PAM4,QAM16,QAM64,QPSK,WFDM | 4                  | 128           | -20dB to +18dB  | 110,000                   | 110,000                  |

The equation for calculating the mean accuracy metric is shown in eqn. (14) and (15):

\[
\hat{v}^{(l)}(N + 1) = \sum_{i=1}^{N} \hat{v}^{(l)}(i) - \sum_{i=1}^{N} \hat{v}^{(l)}(i) \quad (14)
\]

\[
\hat{P}(j) = \frac{\exp(\hat{v}^{(l)}(j))}{\sum_{i=1}^{N+1} \exp(\hat{v}^{(l)}(i))}, j = 1, 2, ..., N + 1 \quad (15)
\]

where \( \hat{v}^{(l)}(N + 1) \) and \( \hat{P}(N + 1) \) represent the activation value and probability of unknown class respectively. Besides, the mean accuracy metric is adopted for all experiments to evaluate the performance.

TABLE I

| Modulations              | Samples per symbol | Sample length | SNR Range       | Number of training samples | Number of testing samples |
|-------------------------|--------------------|---------------|-----------------|---------------------------|--------------------------|
| 8PSK,AM-DSB,AM-SSB,BPSK,CPFSK,GFSK,PAM4,QAM16,QAM64,QPSK,WFDM | 4                  | 128           | -20dB to +18dB  | 110,000                   | 110,000                  |

TABLE II

| Architecture            | Cells per layer | Parameters Number | Training Time | Accuracy (>0dB) |
|-------------------------|----------------|-------------------|---------------|-----------------|
| AF 2 LSTM+1 Dense       | 128            | 200,075           | 1.5h          | 0.8790          |
| IQ 2 LSTM+1 Dense       | 128            | 200,075           | 1.5h          | 0.9006          |
| DC 2 LSTM+1 Dense       | 128            | 400,139           | 2.9h          | 0.9023          |
| DC 2 B-LSTM+1 Dense     | 128            | 1,062,411         | 9.4h          | 0.8977          |

Fig. 2. Open Set Performance Comparison.
open set classes it has never seen while CL-WF model can recognize partial unknown classes. The following paragraphs give out the reason why the proposed model works by visualizing the features output of CL-WF model.

The fully connected layer with two neurons is added between concatenation layer and output layer for visualization convenience. Modified model is retrained in the same way, the feature distributions of training set and testing set with CL-WF model are illustrated in Fig. 3 and Fig. 4, respectively. The black dash circles indicate the known classes areas acquired from training, the other areas represent unknown classes or wrongly classified classes.

From Fig. 3 and Fig. 4 it can be concluded that: firstly, even open set unknown modulations would be clustering into a center; secondly, the centers of unknown classes are different from the known centers, this fact provides opportunity to recognize open set unknown classes. It should be aware that features are two-dimensional which caused extremely information compressed and dimension reduced, whereas this process is not adopted for performance evaluation. In addition, only correctly predicted training examples are used to calculate the centers of each class and the coefficients of different distributions.

IV. CONCLUSION

A new DC-LSTM model, center loss and Weibull distribution based open set automatic modulation recognition algorithm is proposed in this letter. Two matrices are adopted to represent raw modulation signals, a loss function based on cross-entropy and center loss is used to extract separable and discriminative features which are used to fit the Weibull distribution to recognize open set modulations. Proposed algorithm is validated on the public dataset. Quantitative analysis indicates that with no unknown classes, the DC-LSTM model could achieve an average accuracy of 90.2% which achieves the state of the art result. With unknown classes, the performance can be dramatically improved on 14.2%. Experiments results reveal that the proposed algorithm can effectively recognize modulation types even with unknown modulation types. This is the first effort to tackle the automatic modulation recognition under open set circumstance to our best knowledge.

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