Complicated Interference Identification via Machine Learning Methods

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***Abstract*—Under complicated electromagnetic environments, useful signals often interfere with other electromagnetic systems nowadays. Then how to suppress the interferences is a critical problem. Since there is no universal suppression method for each kind of interferences, we need to identify the interferences, and then perform the specific suppression method to tackle with the interferences. In this paper, we simulate 15 types of possible interference signals, some are mixed by two different kinds of interferences, and extract seven features in the time-frequency domain under different interference-to-noise ratios (INRs). By fully analyzing these features, several common classifiers, such as random forest, gradient boosting, and a neural network, are designed to identify these complicated interferences. Numerical experiments are provided to demonstrate the effectiveness of the proposed methods. The final accuracy can exceed 95.20% at the condition INR=20dB.**

***Index Terms*—Mixed interference identification, random forest, gradient boosting, neural network**

I. Introduction

With the widespread use of wireless communication and radar equipment, we now have fewer electromagnetic frequency bands available, and the electromagnetic environment is becoming more complicated. The complicated electromagnetic environment leads to inevitable interferences for each electromagnetic device. To ensure the ability of the devices, such as communication and radar systems, we can enhance the anti-interference capability of our equipment to suppress interferences. Since there is no universal suppression method for each kind of interference, we need to identify the interferences, and then perform the specific suppression method to tackle with the interferences.

Generally, the interference identification problem mainly involves two aspects of research, one is the feature extraction of different interferences and the other one is the research of classifiers. Plenty of researches focused on the feature extraction of interferences, such as wavelet analysis [1], time-frequency image conversion [2], and short-time Fourier transform [3], to obtain various useful features. Previous researches commonly use these features to analyze and identify one individual interference. Some classification and recognition algorithms, using the machine learning algorithm [4], are based on few extracted features, while some algorithms, using the neural network [5], directly used the interferences for classification without feature extraction thus have very high training complexity.

Hence, in this paper, to fit the actual electromagnetic environment, we focus on the identification problem of complicated interferences and simulate mixed interferences, which is not common in previous works. At the first stage, we use features extracted from one single sample of the interferences and then use multiple classifiers to identify interferences. Next, to improve the performance, multiple samples of interferences are combined for feature extraction. The scales of these extracted features are much smaller than the original interference signals. Hence, it can significantly reduce the complexity of training when using these features as the dataset. The experiment results show that the proposed method can realize an accuracy larger than 90% when INR$\geq$5dB.

II. Signal Modeling

Many interferences existed in today's complex electromagnetic environment. For a radar system, commonly occurred interferences are single-tone interference, multitone interference, etc. We classify common interferences into five types, and their mathematical expressions are presented as follows:

A. Single-Tone

Single-tone interference blocks communication and signal detection at one specific frequency point. The power spectrum density of this interference is shown in Figure 1 ßingle-tone INR=20dB", we can see a strong frequency point in the spectrum, presenting the single frequency blocking point.

$$J(t) = Ae^{j(2\pi f_J t+\phi)} \tag{1}$$

B. Multitone

Multitone interference blocks communication and signal detection at several specific frequency points. The power spectrum density of this interference is shown in Figure 1 "multitone INR=20dB", we can see several strong frequency points in the spectrum, presenting the blocking at several frequency points.

$$J(t) = \sum_{m=1}^{M} Ae^{j(2\pi f_m t+\phi_m)} \tag{2}$$

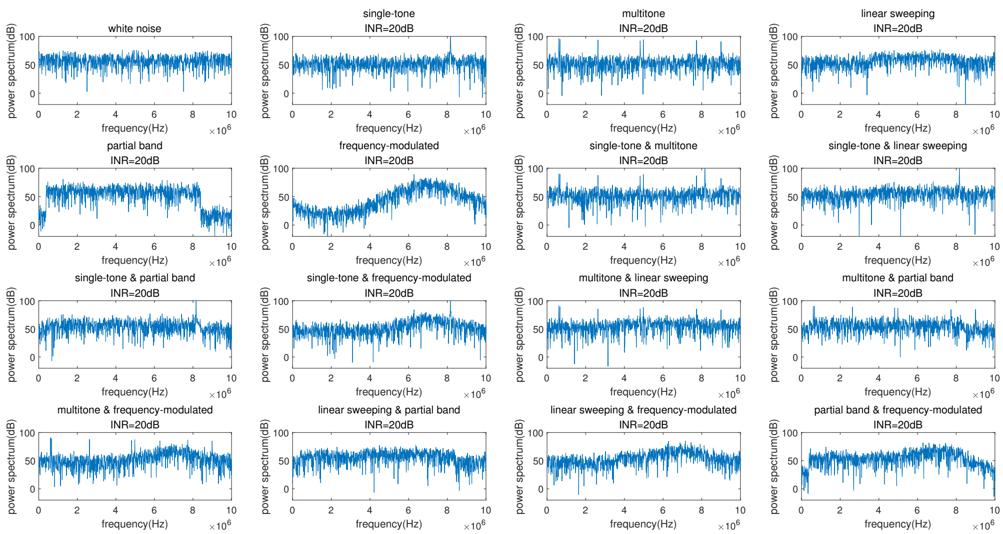


Figure 1. White Gaussian noise and 15 types of interferences

C. Linear Sweeping

Linear sweeping interference, also known as the linear frequency-modulated interference signal, blocks useful communication and signal detection on a continuous frequency band. The power spectrum density of this interference is shown in Figure 1 "linear sweeping INR=20dB". It can be seen that a relatively flat frequency band stands out, presenting the blocking at a wide frequency band.

$$J(t) = Ae^{j(2\pi f_0 t + \pi k t^2 + \phi)} \tag{3}$$

D. Partial Band

Partial band interference signal presents white Gaussian noise on the interference spectrum, blocking useful communication and signal detection on a continuous frequency band. The power spectrum density of this interference is shown in Figure 1 "partial band INR=20dB". It seems similar to the linear sweeping interference with a flat and strong frequency band, but the power spectrum density in the blocking frequency band is Gaussian noise-like, which is different from the linear sweeping interference.

$$J(t) = U(t)e^{j(2\pi f_J t + \phi)} \tag{4}$$

E. Frequency-Modulated

Frequency-modulated interference is a Gaussian distribution power spectrum density signal. The power spectrum density of this interference is shown in Figure 1 "frequency-modulated INR=20dB". It is seen as a wideband interference and the power spectrum density looks like a sinusoidal function.

$$J(t) = Ae^{j2\pi f_0 t + j2\pi k_{jm}\int_0^t \xi(t')dt'} \tag{5}$$

Based on our knowledge, previous researches only focused on the identification problem of several single type interferences. However, it is hard to suggest that only one type of interference exists in a practical circumstances. The cases, where a few types of interferences exist simultaneously and block the working frequency band are more common in the complicated electromagnetic environment nowadays. Therefore, we consider the circumstances of mixed interferences which are combined by two different interferences. In this paper, the powers of two mixed interferences are simply set the same. Then by combining above five basic interferences in order, we have ten types of mixed interferences.We simulate the above 15 interferences and add the white Gaussian noise for blank control. The power spectrum density of each interference when INR=20dB is drawn in Fig. 1 and the names of each type interferences are tagged above each figure.

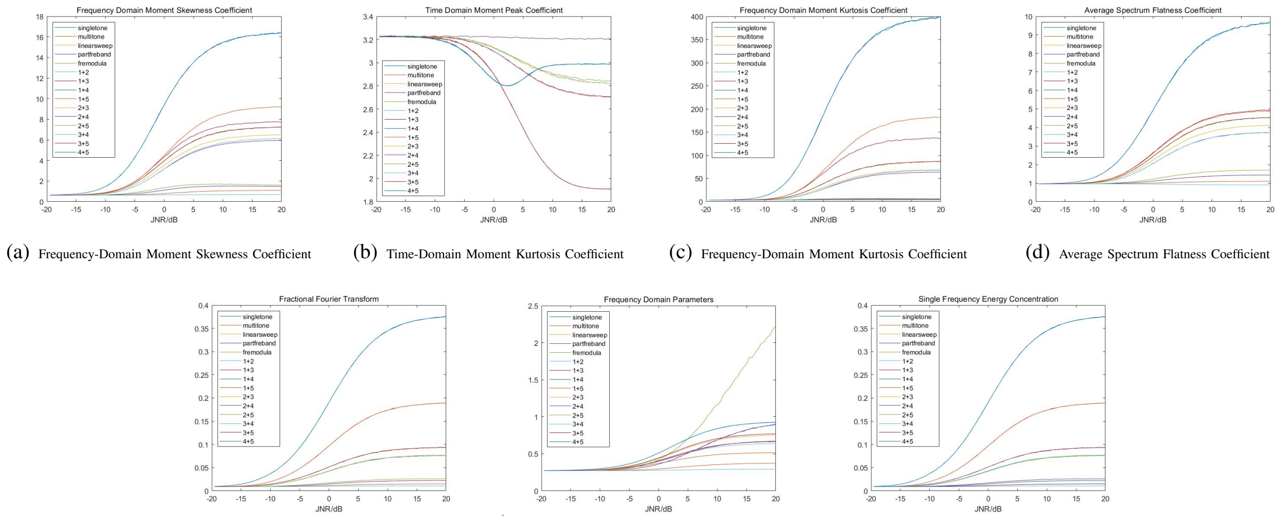
III. Feature Extraction

As analyzed in Section I, we can significantly reduce computational complexity by using features instead of original data. Since the features are required to distinguish each interference from another, the choice of features is critical for the final performance. To be noticed that before feature extraction, power normalization is needed to prevent the amplitude of each interference from affecting the feature values. Herein, we select seven features in both the time domain and frequency domain as follows:

A. Frequency-Domain Moment Skewness Coefficient

The frequency-domain moment skewness coefficient represents the degree of amplitude relative to normal distribution offset in the frequency domain.

$$b_3 = \frac{E(F(n) - \mu)^3}{\sigma^3} \tag{6}$$



(a) Frequency-Domain Moment Skewness Coefficient (b) Time-Domain Moment Kurtosis Coefficient (c) Frequency-Domain Moment Kurtosis Coefficient (d) Average Spectrum Flatness Coefficient

(e) Energy Aggregation Degree of Fractional Fourier Domain (f) Frequency-Domain Parameters (g) Single-Frequency Energy Compaction Measure

Figure 2. Curves of 15 interferences' seven features versus INR

B. Time-Domain Moment Kurtosis Coefficient

The moment kurtosis coefficient in the time domain represents the amplitude steepness of the signal in time domain.

$$a_4 = \frac{E(|X-\mu|^4)}{\sigma^4} \tag{7}$$

C. Frequency-Domain Moment Kurtosis Coefficient

The moment kurtosis coefficient in the frequency domain represents the amplitude steepness of the signal frequency spectrum.

$$b_4 = \frac{E(F(n)-\mu)^4}{\sigma^4} \tag{8}$$

D. Average Spectrum Flatness Coefficient

The average spectral flatness coefficient is the standard deviation of the difference between the original power spectrum and the signal power spectrum after windowed smooth. It is used to indicate the change degree of signal amplitude in the power spectrum domain.

$$P_u(n) = \frac{P(n)}{\overline{P(n)}} \tag{9}$$

$$P_p(n) = P_u(n) - \frac{1}{2L+1}\sum_{i=-L}^{L} P_u(n-i) \tag{10}$$

$$F_c = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(P_p(n) - \overline{P_p(n)})^2} \tag{11}$$

E. Energy Aggregation Degree of Fractional Fourier Domain

The energy aggregation degree of the fractional Fourier domain, representing the energy aggregation degree of the signal in the p-order FRFT domain, is mainly used to search the linear sweep interference. p is selected according to the FRFT domain order corresponding to the largest energy aggregation degree. Obviously, for the linear sweep signal, p should be 2.

$$R_{ft} = \frac{\sum_{e=m-r}^{m+r}|X(e)|^2}{\overline{|X(n)|^2}} \tag{12}$$

$$\overline{|X(n)|^2} = \frac{1}{N-2r-1}\left(\sum_{n=1}^{N}|X(n)|^2 - \sum_{e=m-r}^{m+r}|X(e)|^2\right) \tag{13}$$

F. Frequency-Domain Parameter

The frequency-domain parameter represents the change degree of the spectrum signal envelope in the frequency domain.

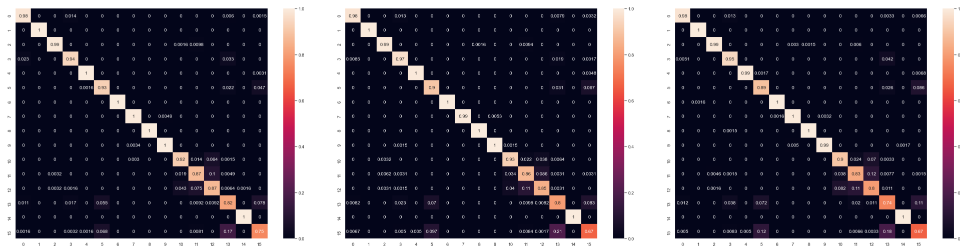
$$R_f = \frac{\sigma^2}{\mu^2} \tag{14}$$

G. Single-Frequency Energy Compaction Measure

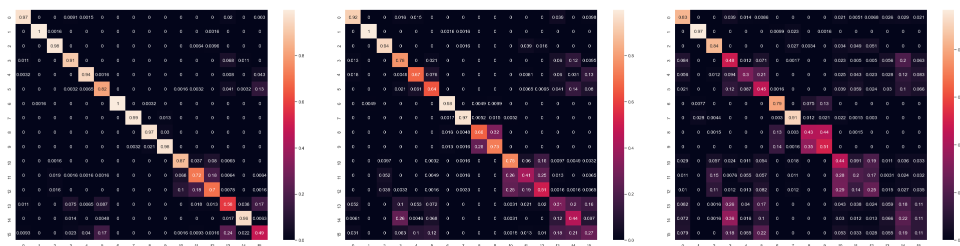
Single-frequency energy compaction measure, representing the energy aggregation of the signal in the frequency domain, is mainly used to distinguish the single-tone interference. The energy aggregation of the signal is calculated by the power of the maximum point of the signal spectrum divided by the total power.

$$C = \frac{\sum_{i=m-k}^{m+k}F^2(i)}{\sum_{i=1}^{N}F^2(i)} \tag{15}$$

The above features are calculated after the sampling process and are finally used for the training of the classifiers. Seven features of 15 types of interferences are calculated at every INR point. The curves of 15 types of interferences' seven features versus INR are shown in Fig. 2. As can be seen, although some types of interferences' features stand out from others, most interferences' features are similar to one another. Hence, it is required to overall consider seven features and identify the interferences.

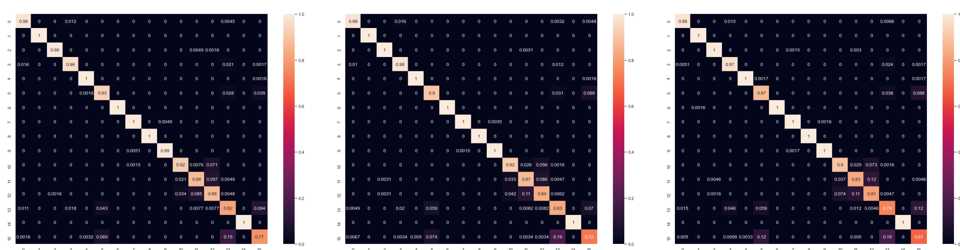


(a) INR=20dB (b) INR=15dB (c) INR=10dB

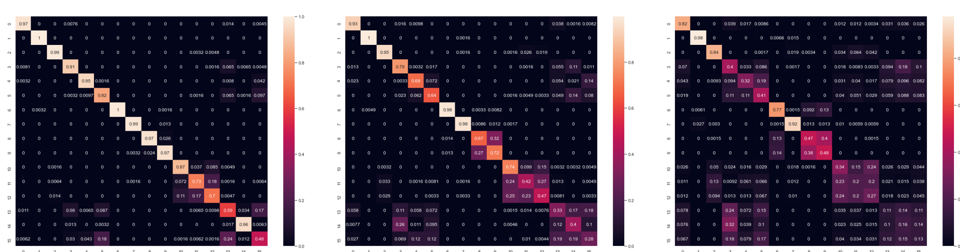


(d) INR=5dB (e) INR=0dB (f) INR=-5dB

Figure 3. Confusion Matrix on Different INR-GBClassifier(dataset-1)



(a) INR=20dB (b) INR=15dB (c) INR=10dB



(d) INR=5dB (e) INR=0dB (f) INR=-5dB

Figure 4. Confusion Matrix on Different INR-RFClassifier(dataset-1)

IV. CLASSIFIER

To consider seven features altogether, three classifiers based on machine learning are used for identification as follows:

Gradient Boosting The first classifier we use is the gradient boosting. Boosting algorithms combine a series of weak learners to boost the prediction accuracy [6]. The algorithm takes all features into account by multiple iterations and forms an overall accurate model.

Random Forest Another classifier we consider is the random forest. Random forest uses a decision tree as the model of bagging[7], sampling both samples and features to avoid overfitting.

Neural Network Deep learning algorithms, based on the neural network framework, have dominated almost all of the computer vision and natural language processing domains. Herein, we consider using the traditional densely connected neural network[8] since the input are extracted features that do not have the locally spatial information or the time-series information.

The neural network model used in this paper is presented as follows: The input layer is a fully connected layer of 100 nodes, the hidden layer is a fully connected layer of 50 nodes, and the output is a fully connected layer of 16 nodes, corresponding to 16 classes of interferences. Next, we will test the effectiveness

Table I
Accuracy of each Classifier under different INR

classifier	dataset	INR=-5	INR=0	INR=5	INR=10	INR=15	INR=20
Gradient Boosting	dataset-1	0.5020	0.6830	0.8600	0.9050	0.9330	0.9440
Random Forest	dataset-1	0.4597	0.6836	0.8700	0.9208	0.9348	0.9438
Neural Network	dataset-1	0.4538	0.6691	0.8586	0.9127	0.9374	0.9446
Neural Network	dataset-2	0.7028	0.8257	0.9262	0.9207	0.9476	0.9522

of the mentioned above classifiers and features.

V. Experiment

In this section, series of experiments are provided. Firstly, the training and testing datasets are prepared as follows.

A. Training Dataset

In dataset-1, we simulate every 15 types of interference signals and white Gaussian noise for blank control with the formulations provided in Section II with 1024 time samples for 5000 times and calculate seven features with 1024 time samples under 6 different setting INRs.

Next, we consider a long-time observation, the interferences are monitoring with 100 times time samples, namely, 102,400-time samples. We divide the total sample points into 100 groups and extract features from each group. Then all the features are re-stacked to be a 7-by-100 feature matrix. Herein, we have more information with a longer observation. Like dataset-1, we also simulate every 15 types of interference signals and white Gaussian noise for blank control for 5000 times under 6 different setting INRs.

B. Experimental Results

The experiment results are shown in Table I, the table presents the algorithm, the dataset, the setting INR, and the experimental results in detail. To analyze the accuracy of three classifiers, we use the confusion matrixes[9] to compare each classifier. The confusion matrixes of the results trained by the gradient boosting classifier with dataset-1 are shown in Fig. 3. The confusion matrixes of the results trained by the random forest classifier with dataset-1 are shown in Fig. 4. The confusion matrixes of the results trained by the proposed fully connected neural network with dataset-1 are shown in Figure 5. The confusion matrixes of the results trained by the proposed fully connected neural network with dataset-2 are shown in Figure 6. The INR condition is mentioned in the above figures.

As can be seen from Table I, the identification accuracy can reach up to 95.22% when INR=20dB under dataset-2 by using the proposed fully connected neural network. The results also show a dramatic decline in identification accuracy when INR$\leq$0dB. It is suggested that we cannot identify the interference under a very low INR with high accuracy, this phenomenon is not ideal but acceptable, for interferences under a very low INR is similar to white Gaussian noise and need no specific suppression method. Compared with the above experiments, the accuracy of the fully connected neural network under dataset-2 is the best at almost every INR value, especially when INR$\leq$5dB. It is suggested that the high accuracy highly depends on a long observation period of the interference signal, which is true for the practical identification problem of one interference signal.

Further, as can be seen from the confusion matrix (Fig. 3 4 5 6), the single-tone interference has high identification accuracy even when INR=0dB, showing that single-tone signal, because of its unique power spectral characteristics, is easy to be recognized. For mixed interferences 10, 11, and 12 (multitone & linear sweeping, multitone & partial band, multitone & frequency-modulated), the recognition accuracy is significantly reduced when INR is very low, this may be caused by the superposition of multitone signals, which makes the other part of the interference features difficult to identify with power normalization. In addition, Linear Sweeping & Partial Band interference signal, and Partial Band & Frequency-Modulated interference signal still have low recognition accuracy when INR is very high because the two mixed interferences cannot be distinguished by the existing combination of features. It is suggested that other features need to be added to distinguish these two kinds of interferences. Compared with the aforementioned three algorithms, it can be noted that the recognition performance of the proposed fully connected neural network is far better than that of the proposed classifier for several specific interferences, like white Gaussian noise, when INR is very low. It is suggested that the proposed fully connected neural network is more robust.

VI. Conclusion and Outlook

This work presented 15 types of interferences, including basic five types of interferences and their mixed ones, and extracted seven useful features. Based on the extracted features, we employed the gradient boosting classifier, the random forest classifier, and the fully connected neural network to identify the interferences. Two different datasets are constructed for training and the confusion matrices were illustrated to show the excellent identification accuracy of the proposed neural network. Our possible future research would emphasize a better neural network under more complicated interference circumstances.

VII. Acknowledgement

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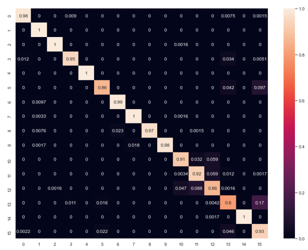
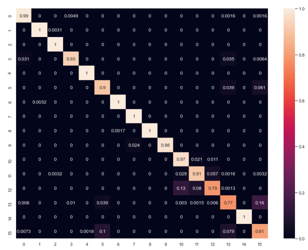
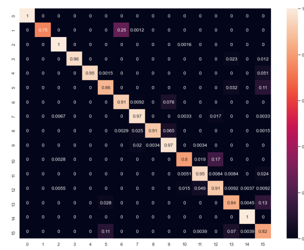


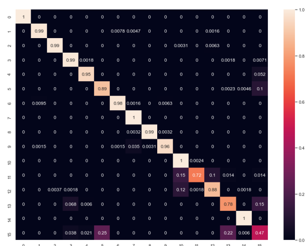
(a) INR=20dB



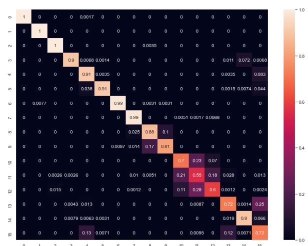
(b) INR=15dB



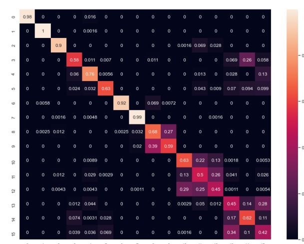
(c) INR=10dB



(d) INR=5dB

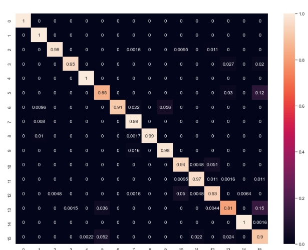


(e) INR=0dB

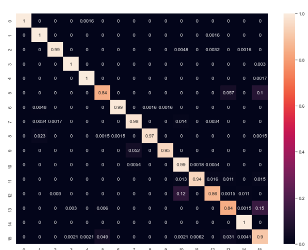


(f) INR=-5dB

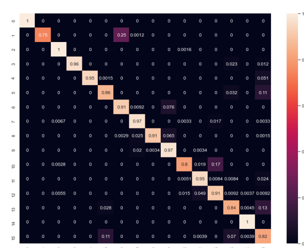
Figure 5. Confusion Matrix on Different INR-Neural Network(dataset-1)



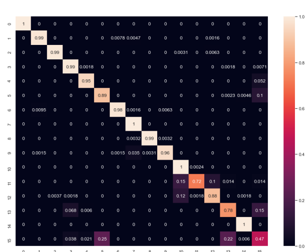
(a) INR=20dB



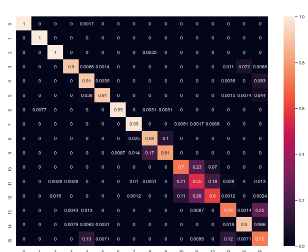
(b) INR=15dB



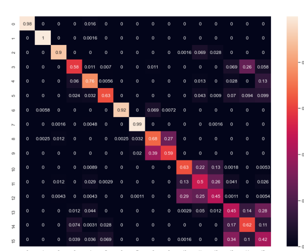
(c) INR=10dB



(d) INR=5dB



(e) INR=0dB



(f) INR=-5dB

Figure 6. Confusion Matrix on Different INR-Neural Network(dataset-2)

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