6409
Complicated Interference Identification via Machine Learning Methods

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Background

- electromagnetic environment is becoming more complicated
- enhance the anti-interference capability of our equipment to suppress interferences
- no universal suppression method for each kind of interference
- identify the interferences, and then perform the specific suppression method to tackle with the interferences

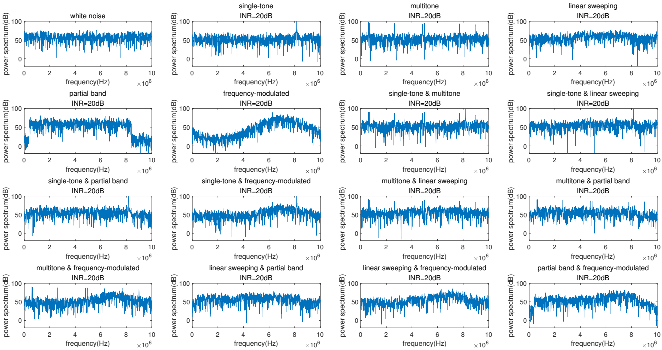
Previous Works

- feature extraction of different interferences
  - wavelet analysis
  - time-frequency image conversion
  - short-time Fourier transform
- research of classifiers
  - machine learning algorithm
  - neural network

Contribution

- simulate mixed interferences
  $\rightarrow$ to fit the actual electromagnetic environment
- multiple samples of interferences are combined for feature extraction
  $\rightarrow$ reduce the complexity of training
- the proposed method can realize an accuracy larger than 90% when INR$\geq$5dB

White Gaussian noise and 15 types of interferences



Math Expressions

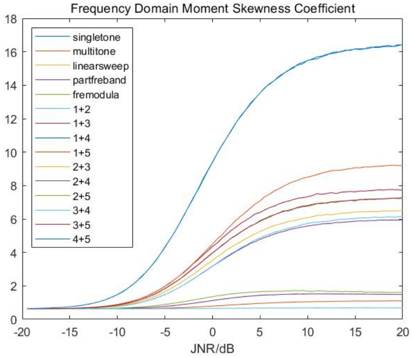
1. Single-Tone:
$$J(t) = Ae^{j(2\pi f_J t+\phi)}$$
2. Multitone:
$$J(t) = \sum_{m=1}^{M} Ae^{j(2\pi f_m t+\phi_m)}$$
3. Linear Sweeping:
$$J(t) = Ae^{j(2\pi f_0 t+\pi k t^2+\phi)}$$
4. Partial Band:
$$J(t) = U(t)e^{j(2\pi f_J t+\phi)}$$
5. Frequency-Modulated:
$$J(t) = Ae^{j2\pi f_0 t+j2\pi k_{jm}\int_0^t \xi(t')dt'}$$

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.

$$b_3 = \frac{E(F(n) - \mu)^3}{\sigma^3} \tag{1}$$

plot

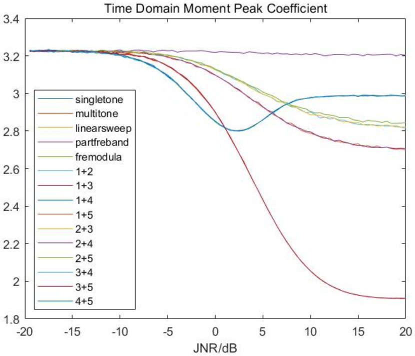

Frequency Domain Moment Skewness Coefficient
singletone
multitone
linearsweep
partfreband
fremodula
1+2
1+3
1+4
1+5
2+3
2+4
2+5
3+4
3+5
4+5
0
2
4
6
8
10
12
14
16
18
-20
-15
-10
-5
0
5
10
15
20
JNR/dB

Time-Domain Moment Kurtosis Coefficient

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

$$a_4 = \frac{E(|X - \mu|^4)}{\sigma^4} \tag{2}$$

plot

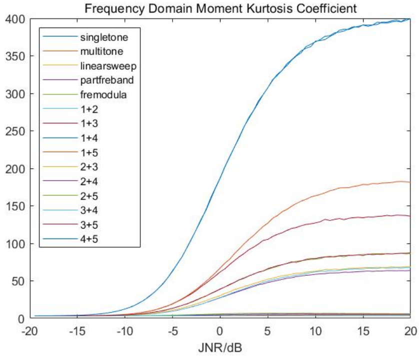

Time Domain Moment Peak Coefficient
3.4
3.2
3
2.8
2.6
2.4
2.2
2
1.8
-20
-15
-10
-5
0
5
10
15
20
JNR/dB
singletone
multitone
linearsweep
partfreband
fremodula
1+2
1+3
1+4
1+5
2+3
2+4
2+5
3+4
3+5
4+5

Frequency-Domain Moment Kurtosis Coefficient

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

$$b_4 = \frac{E(F(n) - \mu)^4}{\sigma^4} \tag{3}$$

plot


Frequency Domain Moment Kurtosis Coefficient
singletone
multitone
linearsweep
partfreband
fremodula
1+2
1+3
1+4
1+5
2+3
2+4
2+5
3+4
3+5
4+5
400
350
300
250
200
150
100
50
0
-20
-15
-10
-5
0
5
10
15
20
JNR/dB

Average Spectrum Flatness Coefficient

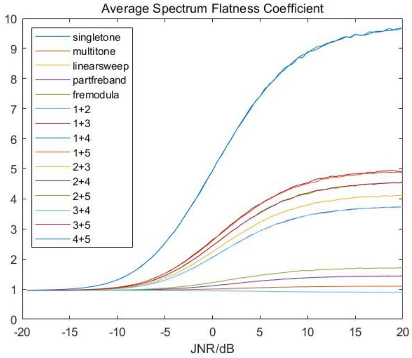
The average spectral flatness coefficient is the standard deviation of the difference between the original power spectrum and the signal power spectrum after windowed smooth.

$$P_u(n) = \frac{P(n)}{\overline{P(n)}} \tag{4}$$

$$P_p(n) = P_u(n) - \frac{1}{2L+1}\sum_{i=-L}^{L} P_u(n-i) \tag{5}$$

$$F_c = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(P_p(n) - \overline{P_p(n)})^2} \tag{6}$$

plot


Average Spectrum Flatness Coefficient
singletone
multitone
linearsweep
partfreband
fremodula
1+2
1+3
1+4
1+5
2+3
2+4
2+5
3+4
3+5
4+5
JNR/dB
0
1
2
3
4
5
6
7
8
9
10
-20
-15
-10
-5
0
5
10
15
20

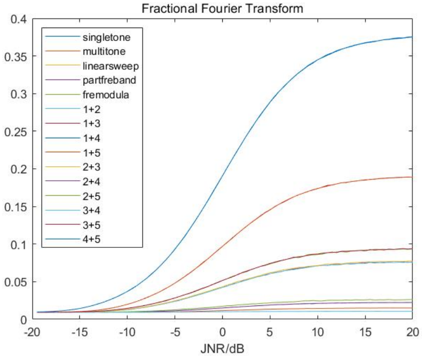
Energy Aggregation Degree of Fractional Fourier Domain

The energy aggregation degree of the fractional Fourier domain, representing the energy aggregation degree of the signal in the p-order FRFT domain.

$$R_{ft} = \frac{\sum_{e=m-r}^{m+r} |X(e)|^2}{\overline{|X(n)|^2}} \tag{7}$$

$$\overline{|X(n)|^2} = \frac{1}{N-2r-1}\left(\sum_{n=1}^{N} |X(n)|^2 - \sum_{e=m-r}^{m+r} |X(e)|^2\right) \tag{8}$$

plot

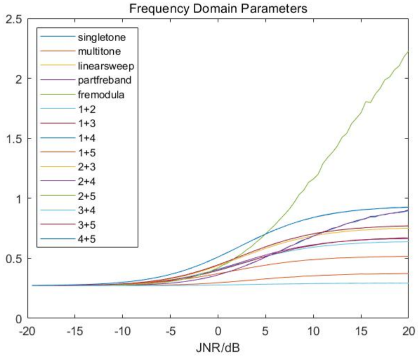

Fractional Fourier Transform
singletone
multitone
linearsweep
partfreband
fremodula
1+2
1+3
1+4
1+5
2+3
2+4
2+5
3+4
3+5
4+5
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
-20
-15
-10
-5
0
5
10
15
20
JNR/dB

Frequency-Domain Parameter

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

$$R_f = \frac{\sigma^2}{\mu^2} \tag{9}$$

plot

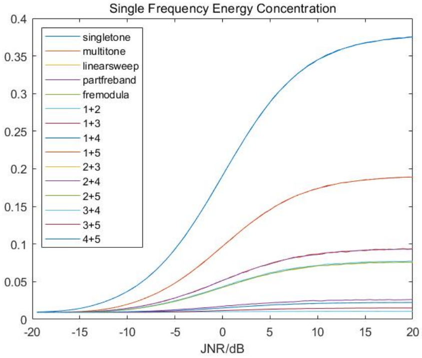

Frequency Domain Parameters
singletone
multitone
linearsweep
partfreband
fremodula
1+2
1+3
1+4
1+5
2+3
2+4
2+5
3+4
3+5
4+5
2.5
2
1.5
1
0.5
0
-20
-15
-10
-5
0
5
10
15
20
JNR/dB

Single-Frequency Energy Compaction Measure

Single-frequency energy compaction measure, representing the energy aggregation of the signal in the frequency domain.

$$C = \frac{\sum_{i=m-k}^{m+k} F^2(i)}{\sum_{i=1}^{N} F^2(i)} \tag{10}$$

plot


Single Frequency Energy Concentration
singletone
multitone
linearsweep
partfreband
fremodula
1+2
1+3
1+4
1+5
2+3
2+4
2+5
3+4
3+5
4+5
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
-20
-15
-10
-5
0
5
10
15
20
JNR/dB

Algorithms

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

- Gradient Boosting
- Random Forest
- Neural Network

Dataset-1

Table: Dimensions of the Dataset-1

stuff	number
number of each interference	5000
type of interference	16
feature	7
number of INR	6

Dataset-2

Table: Dimensions of the Dataset-2

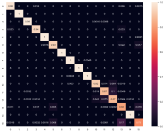
stuff	number
number of each interference	5000
type of interference	16
feature	7
sample time	100
number of INR	6

Accuracy of each Classifier under different INR

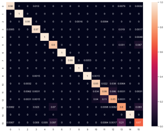
classifier	dataset	INR=-5	INR=0	INR=5	INR=10	INR=15	INR=20
Gradient Boosting	dataset-1	0.5020	0.6830	0.8600	0.9050	0.9330	0.9440
Random Forest	dataset-1	0.4597	0.6836	0.8700	0.9208	0.9348	0.9438
Neural Network	dataset-1	0.4538	0.6691	0.8586	0.9127	0.9374	0.9446
Neural Network	dataset-2	0.7028	0.8257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

- The identification accuracy can reach up to 95.22% when INR=20dB under dataset-2.
- We cannot identify the interference under a very low INR with high accuracy.
- The high accuracy highly depends on a long observation period of the interference signal.

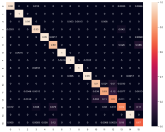
Confusion Matrix on Different INR-GBClassifier(dataset-1)



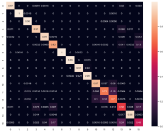
(a) INR=20dB



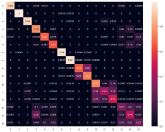
(b) INR=15dB



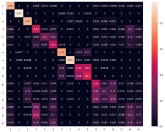
(c) INR=10dB



(d) INR=5dB

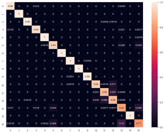


(e) INR=0dB

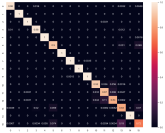


(f) INR=-5dB

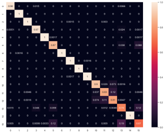
Confusion Matrix on Different INR-RFClassifier(dataset-1)



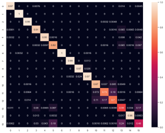
(g) INR=20dB



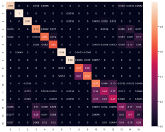
(h) INR=15dB



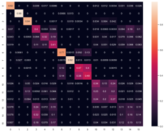
(i) INR=10dB



(j) INR=5dB



(k) INR=0dB



(l) INR=-5dB

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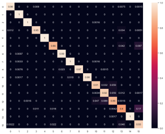
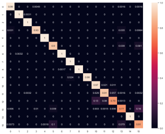
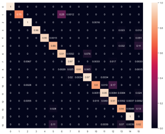
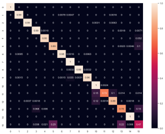
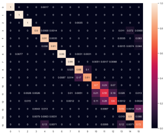
Confusion Matrix on Different INR-Neural Network(dataset-1)

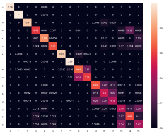

(m) INR=20dB


(n) INR=15dB


(o) INR=10dB


(p) INR=5dB


(q) INR=0dB


(r) INR=-5dB

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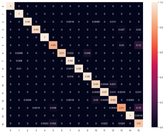
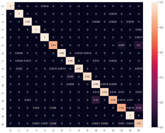
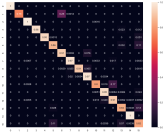
Confusion Matrix on Different INR-Neural Network(dataset-2)



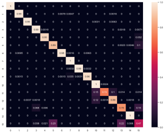
(s) INR=20dB



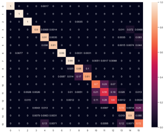
(t) INR=15dB



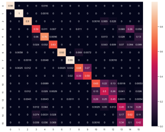
(u) INR=10dB



(v) INR=5dB



(w) INR=0dB



(x) INR=-5dB

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- The single-tone interference has high identification accuracy even when INR=0dB
- For mixed interferences 10, 11, and 12, the recognition accuracy is significantly reduced when INR is very low.
- For mixed interferences 13 and 15, the recognition accuracy is still low when INR is very high.
- The recognition performance of the proposed fully connected neural network is far better than that of the proposed classifier for several specific interferences when INR is very low.

Conclusion

This work

1. presented 15 types of interferences
2. extracted 7 useful features
3. employed 3 algorithms to identify the interferences
4. constructed 2 different datasets for training
5. illustrated confusion matrices to show the excellent identification accuracy of the proposed neural network

Outlook

Possible future research

A better neural network under more complicated interference circumstances.

Acknowledgement

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