辐射源指纹特征提取方法述评(中文/English)

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摘 要：辐射源个体识别是一种仅通过信号的外部特征测量手段，提取辐射源指纹特征，从而识别发射给定信号的特定辐射源个体的技术。近年来，辐射源个体识别技术相关理论与实践应用不断完善，指纹特征提取方法的研究取得了较大的进展。该文在分析国内外大量学术研究成果的基础上，从指纹特征的内在逻辑出发提出了一种新的特征框架。该框架根据不同特征对辐射源指纹的描述特性以及相互之间的关联，将指纹特征划分为直接测量特征和降维变换特征两大类共3个层次，并系统性地梳理了辐射源指纹特征提取方法的研究现状。最后，该文对辐射源指纹特征提取的几个潜在研究方向进行了分析和展望, 希望对辐射源个体识别的研究和应用有所裨益。

关键词：辐射源个体识别；指纹特征提取；模式识别；信号处理；特征框架

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Overview of Radio Frequency Fingerprint Extraction in Specific Emitter Identification (in English)

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Abstract: Specific emitter identification is a technique of extracting the radio frequency fingerprints of the received electromagnetic signal only using external feature measurements to determine the specific emitter that transmits the signal. In recent years, the related theories and practical applications of specific emitter identification have been continuously improved, and research on radio frequency fingerprinting feature extraction methods has made great progress. Based on the domestic and foreign academic achievements, this paper systematically reviews the status quo of the fingerprint feature extraction method of specific emitter identification. In addition, a new feature classification framework is proposed based on the inherent logic of fingerprint feature extraction. The classification framework combines the description characteristics of different radio frequency fingerprinting features and the correlation between them. It divides the existing radio frequency features into two main categories: direct measurement features and dimensionality reduction transform features, which have three levels. Finally, this paper analyzes and explores several potential research directions of fingerprint feature extraction, aiming to benefit the research and application of specific radiation source identification.

Key words: Specific emitter identification; Radio frequency fingerprint extraction; Pattern recognition; Signal processing; Feature framework

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1　引言

辐射源个体识别(Specific Emitter Identification, SEI)，又称辐射源指纹识别或者特定辐射源识别，最早由美国Northrop Grumman公司在20世纪60年代提出[1]，是指仅通过信号的外部特征测量手段，提取出反映目标身份的信息(被称为“辐射源指纹”)，将指纹信息与特征库比对，从而确定发射给定信号的特定辐射源个体的技术。辐射源指纹是发射设备硬件固有特征，具有不可伪造，难以改变，不可避免等特点，以无意调制的形式附加在发射信号上。

SEI技术自诞生之日起，就因具备识别特定发端个体的独特作用，在频谱管理、网络安全、认知无线电以及电子对抗等领域引起了广泛地关注。特别是在军事应用方面，SEI技术能够从复杂的电磁环境中识别特定的信号，并将其与辐射源个体及所属平台和武器系统、战略战术目标关联起来[1]，对于迅速掌握战场态势、把握战争主动权具有重要意义。

辐射源个体识别从接收到的信号时间序列中提取表征特定辐射源个体信息的特征进行分类识别，本质上是一种模式识别问题。Talbot等人[1]在2003年提出了典型的SEI系统结构(如图1所示)，大致的处理流程是：首先通过射频接收子系统接收信号；然后经过信号处理环节，对接收到的信号时间序列进行滤波去噪、脉冲检测等多种预处理，并根据实际需求进行信号解调；再进行指纹特征地提取，获取包含辐射源个体信息的精细特征；最后与数据库进行比对，利用分类识别算法确定发射该信号的特定辐射源，实现对辐射源个体地识别。

在传统SEI(与结合深度学习的智能SEI方法相区分)系统中，指纹特征的定义与提取至关重要。本文将专门针对辐射源指纹特征提取工作进行分析。

本文结构安排如下：第2节简要介绍辐射源指纹特征的基本内涵；第3节简述当前常用的两种分类方法；第4节为本文主要内容，提出了一种更加细致的指纹特征分类框架，详细回顾并分析在此框架下各类指纹特征的研究进展；第5节重点研究人工智能技术应用于辐射源指纹特征提取的现状；最后对辐射源个体识别技术的指纹特征提取进行总结与展望。

2　辐射源指纹特征概述

辐射源发射器件自身的非理想性导致调制信号必然存在偏差，从而携带蕴含硬件信息的无意调制；而不同发射机器件之间存在细微差异，使无意调制隐含了一定的“个体信息”，这种辐射源个体差异由于硬件原因产生、附带在有意调制上，无法避免，难以伪造，即“辐射源指纹”。

然而对辐射源指纹进行描绘和刻画的相关研究挑战性较强，主要有以下3个原因：

(1) 辐射源指纹产生机理复杂，表现上没有生物指纹直观易懂，其本身并没有准确的定义，无法用数学工具精确建模表达；

(2) 辐射源个体之间指纹差异十分细微，特别是同厂家同型号同批次的辐射源个体之间差异极小；

(3) 辐射源指纹是发射信号上附带的无意调制，与信号主要部分相比能量微弱，同时易受复杂信道条件、多径效应、环境噪声的影响。

因此，SEI的实现需要尽可能从更多角度提取有效特征以逼近真实的辐射源指纹。这些特征被称为“辐射源指纹特征”，又叫做“辐射源个体特征”。用于识别辐射源个体的指纹特征必须满足以下5个基本要求[2–4]：

(1) 普遍性：辐射源指纹特征应普遍存在于所有的辐射源个体以及全部信号样本中；

(2) 唯一性：特征参数在不同目标个体的样本中存在差异，即不同辐射源个体的指纹特征是唯一的，各不相同且具有区分性；

(3) 稳定性：同一个目标个体的特征结果在一定时间内稳定不变或者不发生显著变化；

(4) 独立性：辐射源个体特征应独立于信号样式，仅与发射机硬件有关；

(5) 可测性：特征参数能够利用相关技术从观测样本中提取检测出来，且测量精度能够达到个体分类的要求。

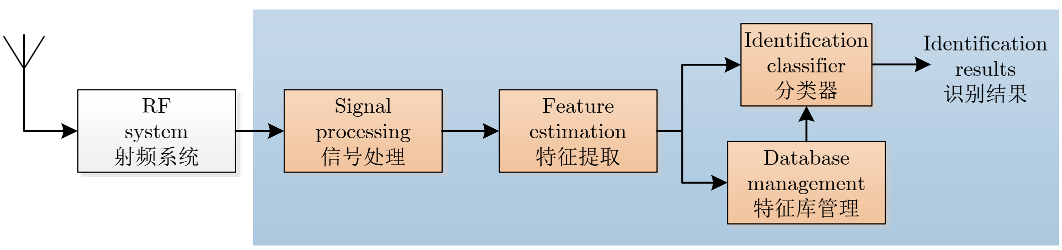


图 1 辐射源个体识别经典系统结构图[1]

Fig. 1 Structural diagram of typical system for specific emitter identification[1]

3 辐射源指纹特征常见分类方法

辐射源指纹特征方法众多，目前研究普遍采用的分类方法有：根据分析对象的信号类型，分为雷达辐射源指纹特征和通信辐射源指纹特征；根据分析对象的信号状态，分为暂态特征和稳态特征。这些分类方法主要是针对SEI的分析对象，没有充分考虑特征对辐射源指纹的描述特性以及不同特征之间的关联。

3.1 通信辐射源指纹特征与雷达辐射源指纹特征

雷达信号的相关研究起步较早，最初将常规雷达参数作为识别依据[1]，其中最典型的是利用脉冲描述字(PDW={RF, PA, PW, TOA, DOA})来识别特定雷达设备。随着雷达体制信号日益复杂，波形设计复杂化；雷达工作频段不断拓宽，不同雷达的工作频段在越来越宽的范围交叠，特别是相控阵雷达、捷变雷达的使用，常规雷达参数已经无法提供足够的有效信息来满足相应的识别需求[5]。雷达信号的脉内特征被越来越多应用于SEI。

相比于雷达信号，通信辐射源的个体识别研究起步稍晚[6]，难度更大：通信信号体制多样、调制类型复杂，携带大量调制信息，细微的指纹特征通常“淹没”在主要信息里，更加难以精准提取。常用的通信辐射源指纹特征有基于信号调制曲线特征、基于高维变换域特征等。

除了传统意义上雷达信号、通信信号外，一些研究开始关注更多类型的信号，例如卫星信号，导航信号，无线网络信号(例如IEEE802.11系列协议信号)，全球移动通信系统(Global System for Mobile communications, GSM)信号，电子标签(Radio Frequency IDentification, RFID)以及其它物联网设备的相关射频信号。

3.2 暂态特征与稳态特征

根据信号状态的固有表现形式，即噪声、暂态、稳态这3部分，与之对应，指纹特征可以分为暂态特征、稳态特征。

暂态是指设备开关机切换、模式变换、数字通信系统码字变换，以及系统外部激励变化等过程。这些过程中的信号不包含任何通信数据，只与设备的物理层特征相关，可以较好体现辐射源的无意调制特性[7,8]。在该过程中提取的指纹特征被称为暂态特征。

暂态特征提取的前提是准确获取暂态信号，然而暂态信号的检测相对复杂，主要面临以下困难：(1)暂态过程持续时间较短；(2)噪声影响下，暂态起点终点不易发现；(3)暂态信号幅度、相位、频率特征容易被非理想的复杂信道情况所影响[9]。Guo等人[10]对典型的暂态分析方法进行比较，重点分析了分形特征、熵、能量轨迹、固有上升沿形状等5种暂态特征。

稳态信号是指发射设备在功率稳定后发射的信号部分，对通信信号而言主要包含需传输的数据部分以及少量的噪声。相较于暂态信号，稳态信号易于获取，但是在辐射源稳定工作状态下，个体的差异是辐射源内部众多的硬件单元(元器件或模块)以“合力”形式表现在信号上，稳态指纹特征在数据与噪声中间“隐藏”更深，更加难以提取。

4 基于指纹分析内在逻辑的特征框架

本文从辐射源指纹特征提取的内在逻辑出发，结合特征工具的数学原理，根据特征提取的思路方法，总结出一种新的指纹特征框架，将现有的指纹特征划分为两大类，即直接测量特征(初级特征)与降维变换特征(2次特征)；再结合指纹特征分析原理，对每个大类进行更加细致的分类，共分为3个层次。

直接测量特征是指基于基本的信号分析过程(基本参数信息、基本变换信息等)，直接针对接收信号时间序列提取的特征。通常情况下，直接测量特征的输入只能为经过预处理后的信号时间序列；直接测量特征结果可以直接与特征数据库比对用于个体识别，而维度较高的特征也可以进一步进行2次特征变换，将计算后的最终结果(即降维变换特征)，作为指纹特征。

降维变换特征与信号特性结合并不紧密，不依赖电磁信号分析的基础知识，不过多考虑信号特性，通常只是作为一种特征描述方法，对直接测量特征进行优化，即在直接测量特征基础上基于一定的数学变换进一步提取的指纹特征。特殊情况下也可以直接用于提取原始信号的特征。

为方便理解与讨论，令$x(n)$表示经过预处理的数据，$F_1\{\cdot\}$为直接测量特征计算，$F_2\{\cdot\}$为降维变换特征提取，用$y(m)$表示最终指纹特征结果，即分类器的输入。常见的提取指纹特征提取思路为

$$y_1(m_1) = F_1\{x(n)\}, \qquad m_1 = 1,2,\cdots,M_1 \tag{1}$$

$$y_2(m_2) = F_2\{F_1\{x(n)\}\}, \quad m_2 = 1,2,\cdots,M_2 \tag{2}$$

其中，y_1, y_2分别表示直接测量特征和降维变换特征，$M_1, M_2(M_2 \le M_1)$为对应的特征维度。然而，理论上也可以直接提取信号$x(n)$的降维变换特征，即$y_2(m_2) = F_2\{x(n)\}$，例如直接计算信号的分形维数用于辐射源个体识别。实际应用中这种情况相对少见，而且通常需要满足一定的前提条件，如针对的特定信号样式或者经过特定的处理等。在本文所

提特征框架下，此类依赖信号特殊结构以及基本信号分析方法的特征被划归于直接测量特征，因此在严格意义上，上述情况可以用式(2)表示。简言之，$F_1\{\cdot\}$, $F_2\{\cdot\}$两者串行，通常先$F_1\{\cdot\}$后$F_2\{\cdot\}$且某些情况下可省略$F_2\{\cdot\}$。

与原有方法相比，该框架细化了指纹特征的分类，其分类逻辑与指纹特征处理分析的内在逻辑相符，从而在保证涵盖现阶段所有常用指纹特征的基础上，尽可能减少重叠，并便于研究人员对指纹特征进一步地细化改进与组合研究。

下面对该分类框架以及各类目下指纹特征的发展现状进行详细地分析。在基于指纹分析内在逻辑的分类框架下，两大类特征如表1、表2所示，其中表1为直接测量特征，表2为降维变换特征见4.2小节。

4.1 直接测量特征

直接测量特征是指与常见的信号基本分析方法息息相关的辐射源指纹特征，此类特征最主要特点是直接作用于预处理信号，尽可能多地获取或者保留原信号的指纹信息。本文主要考虑以下5个方面的辐射源指纹直接测量特征：

表 1 基于指纹分析内在逻辑的指纹特征分类框架下的直接测量特征

Tab. 1 Direct measurement features under the feature framework based on the inherent logic of fingerprint feature extraction

特征方法		相关文献
基本参数信息	常规参数	文献[1,11,12]
	包络特性	文献[13—18]
	瞬时特性	文献[19—23]
	调制参数	文献[24—26]
	频谱分布	文献[3—27]
基本变换信息	时频谱	文献[28—32]
	高阶谱	文献[33—37]
	循环谱	文献[38,39]
	Hilbert谱	文献[40—43]
信号特殊结构	信号导头	文献[23,44,45]
	雷达信号分析	文献[46—51]
分解重构信息	经验模态分解	文献[42,43,52—55]
	固有时间尺度分解	文献[56—63]
	变分模态分解	文献[9,43,64,65]
	相空间重构	文献[2,66—69]
	信号分割重构	文献[70—71]
发射机硬件特性	等效电路	文献[72]
	非线性电路	文献[73]
	频率源	文献[74]

基本参数信息：常用的通信信号参数、雷达信号参数、时域频域基本参数信息，以及其他在常规信号处理过程中选用的可以标识个体信息的参数；

基本变换信息：基本的信号变换，包括时频变换，高阶谱分析，循环谱分析等；

信号特殊结构：为满足特定通信需求或依照相应标准，部分发射信号所含有的特定结构，如IEEE802.11系列协议信号帧头，数字电台传输中的握手信号等；

分解重构信息：对接收的时间序列进行相应变换以提升数据维度，包括自适应信号分解方法、相空间重构方法等；

发射机硬件特性：针对信号发射过程中相关硬件的非理想特性，进行的指纹特征产生机理建模分析。

4.1.1 基本参数信息

基本参数信息指信号的部分常规参数，例如雷达信号的常规参数(如PDW)、包络形状、上升沿时间以及包括瞬时频率、瞬时相位在内的脉内特征等；通信信号的码元速率，载频偏差、频谱特性、调制参数、调制域误差(包括IQ不平衡以及星座图偏移)等。此类特征主要是集中在时域与频域，常见于各类信号处理流程。相比其他信号处理过程，辐射源个体识别对此类参数估计的精度要求通常更高。

本文将基于基本参数信息的指纹特征分为5类：常规参数、包络特征、瞬时参数、调制误差以及频谱分布特征。下面分别介绍它们在辐射源个体识别技术中的应用情况。

(1) 常规参数。基于常规雷达参数特征的辐射源识别技术主要依赖信号测量与检测系统直接测量或估计得到的特征[1,11]，如：载频、脉冲方位角、脉冲编码方式、脉冲宽度、脉冲到达时间、脉冲幅度等，而后与数据库中已知信号参数比对[12]获得截获脉冲信号的相关信息。早期雷达体制较为单一，电磁信号密度较小，脉冲信号频域跨度小且少交叠，信号形式简单且参数较为稳定，因此基于常规参数特征进行相应信号识别在早期的电磁环境中是有效的。如今电磁环境日益复杂、信号多样化，信号参数差异不断缩小，将常规参数直接作为指纹特征难以实现辐射源个体的精确确认。

(2) 包络特征。由于电子设备本身具有“非理想性”，发射机性能不可避免地存在微小差异。这种细微差异能够映射在信号时域脉冲包络形状上，使波形附带特定发射机个性化的特征，可以作为个体识别的依据。雷达辐射源信号脉冲包络波形如图2所示。

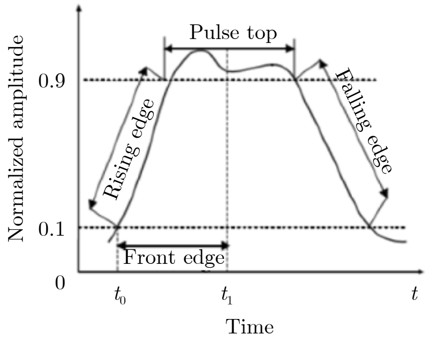


图 2 雷达脉冲包络

Fig. 2 Radar pulse envelope

接收到的辐射源信号受到多径效应和发射机相位噪声以及加性噪声等因素的共同影响，其脉冲包络会产生各种不同程度的失真、衰落[13]。多径效应的影响较大时，脉冲包络形状甚至会发生改变。研究发现，脉冲包络上升沿是包络参数中最不受多径影响的，因此，包络前沿(包括上升沿和部分脉顶波形)常作为辐射源指纹特征[14,15]。

文献[16]结合小波变换技术进行包络分析，提取更高精度的包络信息作为辐射源指纹特征；在文献[14]中，刘旭等人结合递归度分析方法(recurrence rate analysis) 对雷达信号的脉冲起始点及终点进行检测，并新定义了拟合上升角、拟合下降角、P/S 3种变量刻画脉冲包络形状，取得了相对不错的效果。文献[15]中包络R特征和J特征在一定程度上挖掘了信号包络的寄生调制(spurious modulation)的杂散特性。而Rehman等人[17]利用短时傅里叶变换谱图检测蓝牙(bluetooth)信号的暂态能量包络曲线，提取曲线面积、持续时间、最大斜率、峰度、峭度、斜度、方差等特征参量描绘包络细微特性；文献[18]定义了4种包络特征LE, SE, QE, TE。

值得注意的是，雷达脉冲波形易受大气传播效应的影响，会使附带调幅成为不可靠的参数。

(3) 瞬时特征。瞬时特征包括瞬时频率(IF)、瞬时相位(IP)、瞬时幅度(IA)等。瞬时参数的估计方法主要有希尔伯特变换(Hilbert Transform, HT)、能量间隔(Energy Separation, ES)、广义零交点(Generalized Zero-Crossings, GZC)、经验AM-FM分解(empirical AM-FM decomposition)、直接求积(Direct Quadrature, DQ)、归一化希尔伯特变换(Normalized Hilbert Transform, NHT) 等[19]。其中，希尔伯特变换法(HT)最为常用。

瞬时特征主要运用于信号的暂态过程以及帧头结构(preamble)。这些过程的幅度、相位、频率随时间的变化规律往往不同。图3展示了4架民航飞机与地面通信时雷达辐射源发射2次应答信号时的IF特征图像。Hall等人[20]从暂态过程的IF, IP, IA中提取了多项特征，包括：归一化瞬时频率、相位和幅度的标准差，均值归一化瞬时幅度、相位的标准差，同相数据标准差、正交数据标准差等。文献[21]基于瞬时幅度定义五维特征矢量，有效实现对无线网卡和蓝牙设备识别；黄渊凌等人[22]专门针对FSK电台个体识别问题，完成FSK频率畸变特性参数的估计，建立了基于瞬时频率的指纹信号模型；文献[23]结合包络和瞬时相位提取雷达信号个体特征，并基于实测数据分析了雷达工作模式对个体特征的影响。

(4) 调制参数。基于调制域误差的指纹特征又被称为星座图(constellation shape)误差指纹特征。它是由Brik等人[24]在2008年提出的一种稳态指纹特征(即，PAssive RAdiometric Device Identification System, PARADIS)。该方法考虑了器件多种非理想特性对调制信号的影响，包括I/Q路的偏移、频率偏移、限幅作用等，在调制域内通常表现为星座图恶化。不同辐射源硬件设备中振荡源、混频器和功率放大器等器件的非线性特性会有细微差异，信号的星座图形状因此不同，根据星座图形状的差异特性就可以判别信号来自哪个辐射源。

Brik等人[24]对比星座图上散点分布差别，定义了相位误差、幅度误差、I/Q路偏移等指纹特征，成功实现了对138个无线网卡(QPSK调制)的识别。文献[25,26]在Brik等人工作的基础上，对调制域误差有了进一步的研究。其中，文献[25]在载波恢复、符号速率估计和定时估计的基础上进行星座图提取，并通过Hausdorff距离进行相似性度量，识别信号发射设备；文献[26]分析了相位噪声对调制域的影响，利用样本与核的相似性度量，对接收信号观测点动态聚类，得到重构星座图，依据最大似然准则完成星座图分类。

基于星座图误差的指纹特征摆脱了对信号时域波形的依赖，一定程度上抑制了噪声和恶劣通道的影响，易于硬件实现。其缺点同样突出，首先只适用于数字调制信号；其次需要准确估计频率、码速率和调制样式等信息，识别效果很大程度上依赖数字解调的结果。

(5) 频谱分布。不同辐射源个体晶振器产生的信号基准频率存在差异，这种差异造成信号的载频与码速率偏差不同，而相对偏差(偏差与标准差的比值)与标准差无关。文献[3]中，作者研究了精确估计载频以及码速率的方法，并验证了频率偏差作为指纹特征进行辐射源个体识别的有效性。

尽管载频与码速率的相对偏差有一定的分类能

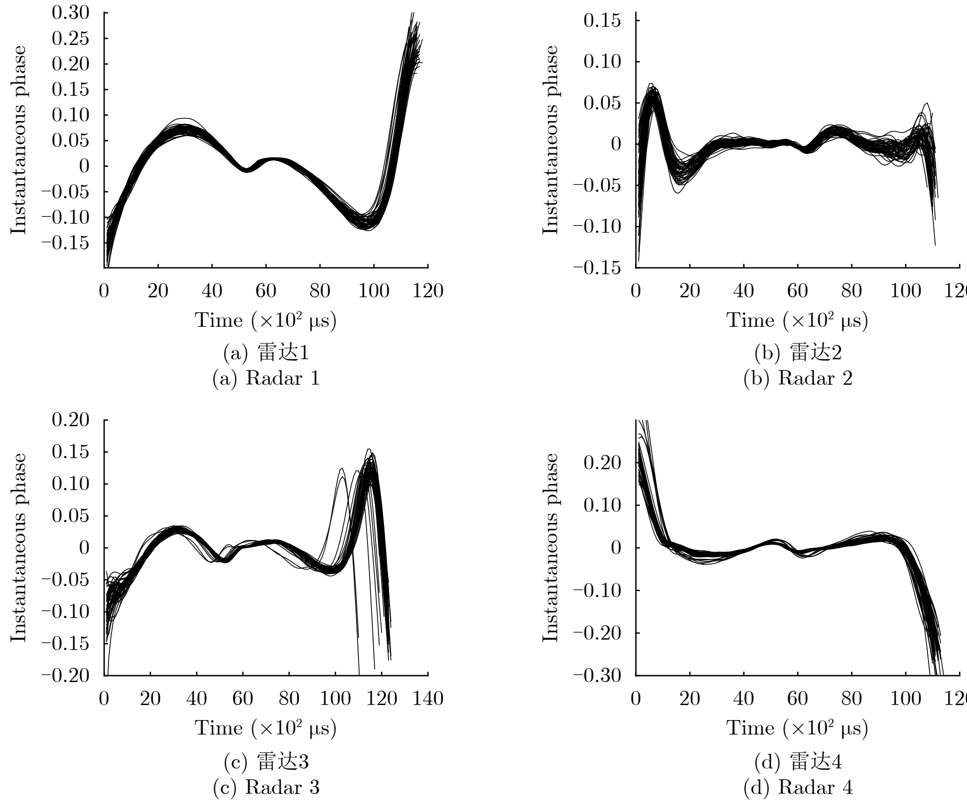


图 3 4架民航飞机2次应答信号瞬时相位

Fig. 3 Instantaneous phase characteristics of the secondary response signals of four civil aviation aircrafts

力，但是SEI的实现要求测量精度在$10^{-6}\sim10^{-7}$量级，而且实际应用中难以获知信号参数的标准值，从而无法计算相对偏差。

除此之外，频谱的非对称特性也可以作为指纹特征，进行辐射源个体的识别[27]。

4.1.2 基本变换信息

在基本参数的基础上，时频谱、高阶谱、Hilbert谱等变换域信息近来被广泛用于辐射源个体识别。

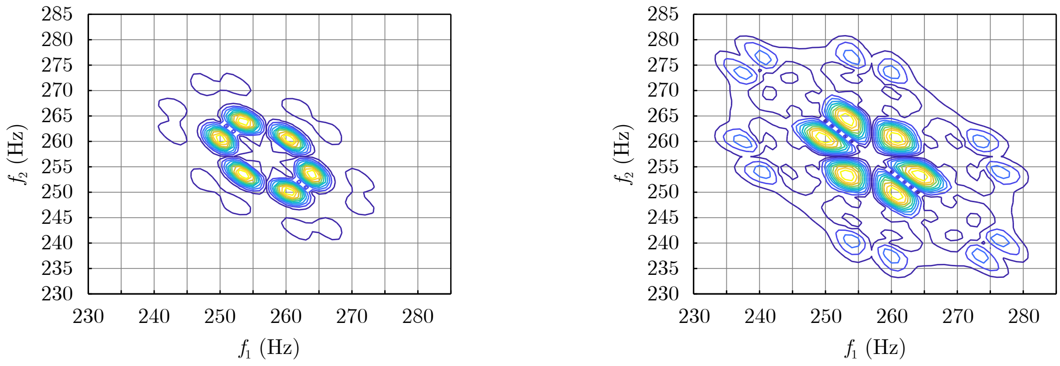
(1) 时频域。信号的时频分析，即时频联合域分析(Joint Time-Frequency Analysis, JTFA)，提供了时间域与频率域的联合分布信息，清楚地描述了信号频率随时间变化的关系，是分析时变非平稳信号的有力工具。常用的时频分析方法有：短时傅里叶变换(Short-Time Fourier Transform, STFT)，小波变换(wavelet transform)，魏格纳分布(Wegener distribution)，二次时频分布(Bilinear TFD)等。

文献[28]分析了短时傅里叶变换(STFT)下的指纹特征；文献[29]系统地分析了二元信号的时频特性；文献[30]中则利用小波变换提取RFID的无意调制特性；美国海军研究生院[31]系统分析了基于小波变换的发射机识别；文献[32]引入Wigner-Vile分布改进后的Choi-Williams分布(Choi-Williams Distributon, CWD)，使用CWD将雷达辐射源信号从一维时域信号转换为二维时频域的时频图像，提取时频图像中的调制特征。

此类指纹特征往往受限于时频工具自身的弊端，从而面临一系列问题。例如，STFT在解决非线性问题上有先天不足，窗函数的选择及其长度与频谱图分辨率之间存在矛盾；小波变换依赖小波包的选择，缺乏精度高、自适应程度高的方法；二次型时频分析方法存在严重的交叉项，整个时频平面的能量可能出现负值。

(2) 高阶谱。实际信号并非严格服从高斯分布，不同辐射源个体发射的信号呈现非高斯性特征。高阶谱(high-order spectrum) 作为高阶累积量(high-order cumulants)的傅里叶变换，是一种有效的非高斯分析工具。高阶谱与时间无关，能够保留信号的幅度和相位信息，抑制高斯噪声。其中3阶谱，又被称为双谱 (bispectrum)，具有时移不变性、尺度变化性、相位保持性的特点，在SEI中应用最为广泛。图4展示了两部FM电台信号的双谱特征分布，由图可知不同辐射源个体信号的双谱特征存在显著差异。

双谱特征是3阶统计特性，算法复杂度较大，且个体特征信息被分散到高维空间，给分类识别造



(a) 电台1
(a) Radio 1

(b) 电台2
(b) Radio 2

图 4 两部FM电台信号双谱特征图

Fig. 4 Bispectrum characteristic images of two FM radio signal

成困难。因此，在选用高阶谱特征时，通常需要结合以切片积分等方式为代表的降维变换特征，根据高维谱线数据分布进行提取降维。

文献[33–37]均选用高阶谱作为初步的高维特征，并选用不同的数学工具进行特征2次提取。文献[3]利用局部线性嵌入(Locally Linear Embedding, LLE)流形约简对高维矩形积分双谱(Square Integral Bispectra, SIB)特征进行降维分析，并针对辐射源识别的特点改进了LLE样本点距离定义和输出维数估计方法。

(3) 循环谱。循环平稳特性(cyclo-stationarity)是调制信号的重要特性，循环谱密度函数包含与调制信号相关的频率和相位等信息，循环谱(cyclic spectrum)分析可以在很大程度上将信号与不具有循环平稳特性的平稳噪声区分开。因此循环谱分析的抗干扰、信号分析表征能力相比功率谱更强[38]。最常用的非参数化循环谱估计方法为时域平滑周期图法和频域平滑周期图法。

文献[39]采用循环谱手段，循环谱密度f=0时的α截面谱(循环谱切片)作为初始高维特征，分析信号中的循环谱差异，从而达到辐射源个体识别的目的。

(4) Hilbert谱。Hilbert谱源于希尔伯特-黄变换(Hilbert-Huang Transform, HHT)，将信号经验模态分解后得到的若干本征模态函数(Intrinsic Mode Function, IMF)进行希尔伯特变换(Hilbert Transform, HT)。希尔伯特变换后可以得到IMF时间、频率、振幅三者之间的关系，其中振幅在时间-频率平面上的分布即Hilbert谱$H(t,\omega)$。

王欢欢等人[40]利用改进后的HHT算法计算信号Hilbert时频谱；王丽[41]总结了部分在HHT基础上可以提取的指纹特征；文献[42]提取了Hilbert边缘谱；文献[43]则关注了HHT指纹特征在单跳场景(single-hop scenario)与中继场景(relaying scenario)以及不同信道下的表现。

4.1.3 信号特殊结构

某些信号本身含有独特的结构特点，可以用于指纹识别。如802.11协议下的无线信号帧头(preamble)，又称为导头，其格式如图5所示。同一标准下，preamble包含的内容相同，能够避免调制信息不同带来的影响，而且相比其他特征更加稳健，适合不同无线网络设备的识别。

文献[23,44]利用Wi-Fi信号preamble进行无线网卡的识别，文献[45]利用7部软件无线电外设发射机(Universal Software Radio Peripheral, USRP)结合协议仿真生成的信号进行识别，取得了不错的效果。然而，大量信号并不具备帧头结构，而且非合作情况下通常无法获取完整的数据帧头。

与preamble类似，雷达信号也有专门的可以用于识别的结构或者参数，如模糊函数(Ambiguity Function, AF)、多普勒(Doppler)[46]。其中，模糊函数最早用于雷达分析和波形设计，现在也常用于表征不同信号的个体差异。文献[47]通过提取模糊函数的主脊切片进行雷达信号分选。文献[48]在文献[47]的基础上提出了局部模糊函数切片以及其快速估计算法，对不同雷达脉冲数据进行提取和识别。王磊等人[49–51]对模糊函数特征进行了进一步的优化。

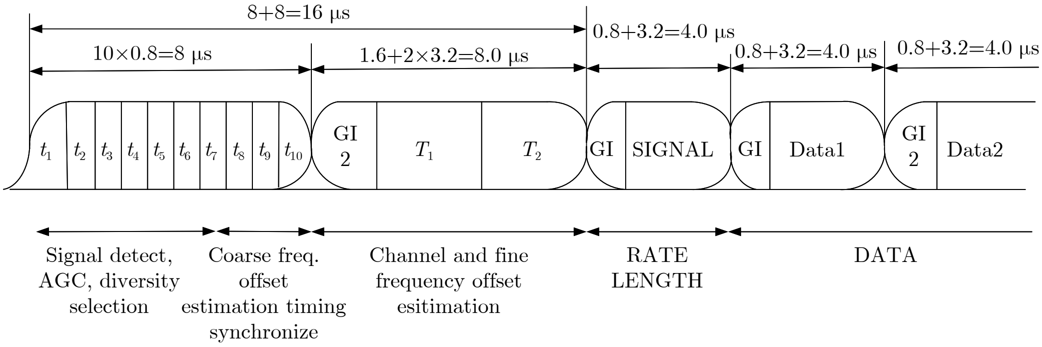
4.1.4 分解重构信息

SEI并不关心信号传输过程中传递的主要信息，反而关注信号主要成分之外的诸多细节。利用分解重构算法提高原始信号维度，可以从更高层面提取指纹相关特征，同时为分离信号的主要成分和次要成分(杂散成分)提供了一种新思路。

常用的分解方法有经验模态分解EMD，固有时间尺度分解ITD，变分模态分解VMD等。重构方法有相空间重构、分割重构等。

PLCP Preamble		PLCP Header			Whitened PSDU
SYNC	Start Frame Delimiter	PLW	PSF	Header Error Check	

(a) 导头格式
(a) Preamble frame format



(b) 导头同步部分结构
(b) Synchronization (SYNC) structure of preamble

图 5 IEEE802.11b协议的导头格式

Fig. 5　Preamble format of standard IEEE802.11b

分解重构使得数据的维度更高、变量更多、形式更加复杂，因此在高维空间中去理解不同信号成分之间的区别与联系，提取真正有意义的信息是利用此类特征实现辐射源个体识别的关键。否则，将数据映射到高维空间只能意味着更大的运算压力、更多的信息冗余。

(1) 经验模态分解EMD。经验模态分解(Empirical Mode Decompo-sition, EMD)最早由Norden等人[52]在1998年提出，是一种针对非线性非平稳信号的后验性自适应时频分析方法。

基本计算方法是，利用3次样条插值方法不断迭代寻找原信号局部最大值最小值点的拟合上下包络线，得到本征模态函数(IMF)分量，完成分解过程。图6展示了EMD分解后某信号以及所有分解分量IMF的时域波形，第1层子图为原信号波形，其余子图分别对应各个IMF。由图6可见，EMD基本上是按照频率由高到低进行分解。其中频率较高，幅值较低的前几层IMF分量，可被粗略理解为附带在该信号上的高频杂散分量。

近20年来，国内外已有诸多基于EMD的SEI研究。文献[53]首先将EMD用于辐射源指纹分析，并与wavelet对比；文献[54]利用IMF重构稳定的时频分布特征；梁江海等人[55]利用EMD将信号的主要成分和包含个体特征的杂散成分分离；文献[42]提取IMF时域和频域的分形特征，结合瞬时频率和Hilbert边缘谱作为指纹特征；文献[43]基于EMD分解提出3种不同特征，并且首次探究了中继场景下的特征表现。

(2) 固有时间尺度分解ITD。2007年，Frei M G等人[56]提出了另一种自适应信号分解方法，固有时间尺度分解(Intrinsic Time-scale Decomposition, ITD)。该方法将信号分解为若干的固有旋转分量和一个单调趋势的和，与EMD相比，减去了筛选和插值的过程。

文献[57]利用ITD分解的瞬时参数重构时频谱，定义信号频谱的谱对称偏离系数作为特征；文献[58]提取了ITD分解后不同旋转分量的分形特征和RJ特性以及边缘谱特性；文献[59]将ITD算法与非线性分析方法结合，利用相关系数筛选出合适的信号分量，提取出了每层信号的熵值数据。任东方等在文献[60]中，将ITD分解和图像处理方法结合提取相应的指纹特征。除此之外，ITD在生物信号[61]、故障诊断[62]、系统检测[61,63]等领域也有着广泛的应用。

(3) 变分模态分解VMD。变分模态分解由Dragomiretskiy等人[64]在2014年提出，是一种在时域频域同时非递归自适应的准正交信号分解方法，在非线性信号分析中有重要作用[65]。VMD方法结果稳定，计算简单，无模态混叠问题；分解出的基本分量IMF有AM-FM调制窄带信号的特点，其瞬时频率有实际的物理意义。对于辐射源信号分析而言有天然的优势。Satija等人[9]在文献[43]的基础上将VMD应用到指纹识别问题，构造VMD熵(VMD-Entroy)和累积量(VMD-EM^2)作为指纹特征。

(4) 信号重构。接收到的信号可以理解为携带传输信息与指纹特征的高维数据投影形成的一维时间序列，因此探究信号的重构，又可以称做升维恢

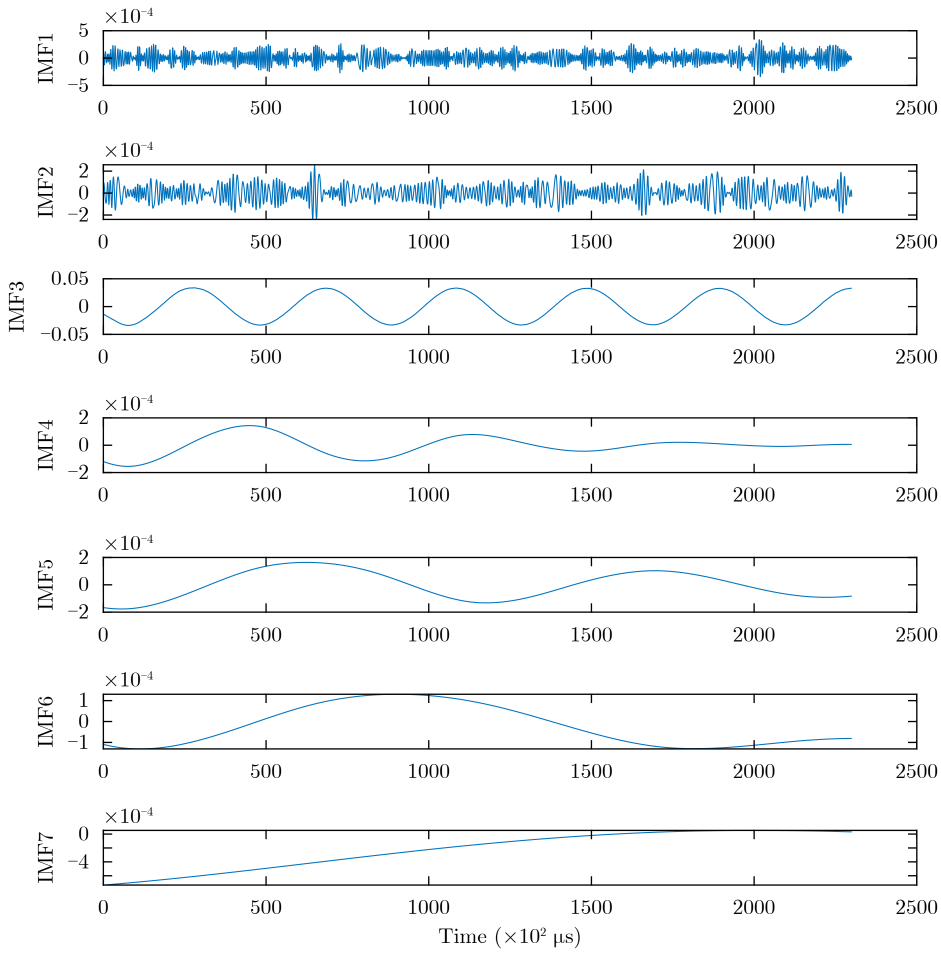


图 6 经验模态分解结果示意图

Fig. 6 Schematic of empirical mode decomposition results

复。常用的重构方法有：利用信号非线性特征相空间重构；分割重构，或者是将参数转化为图像。

相空间分析是非线性动力学的基本分析方法，相空间中的每个相点对应着动力学系统的一个状态，相点变化对应着系统的状态演变。利用时间序列来构造与系统原相空间等价的相空间，即相空间重构，是动力学系统方法分析时间序列非线性的首要步骤[66]。

理论上，不同的发射机对应着不同的非线性系统，重构的相空间中必然存在着特定发射机固有的硬件指纹特征。Carrol[67]首先利用相空间重构方法来解决辐射源指纹识别问题。许丹[2]、袁英俊[68]、朱胜利[69]分别在他们的博士论文中就相空间理论在SEI上的应用进行了详细的讨论。

除了相空间重构外，国内外学者们也进行了其他分割重构方式的尝试。例如，T.J. Bihl等人[70]提出了一种基于滑动窗函数的信号分割和特征向量组合方法；Zhu等人在文献[71]中，将时间序列信号重构为水平可视图(HVG)。

4.1.5 发射机硬件特性

指纹特征机理分析是辐射源指纹识别的重要研究内容，对探索信号指纹特征的物理本质、提取有效的指纹特征具有重要意义。

文献[72]从硬件结构入手，针对含自激振荡器的发射机，构造射频振荡器的等效电路模型，提出模型化的辐射源个体识别技术，在调制电压发生较大变化时，该方法能弥补传统上升沿、下降沿时延测量方法的不足。徐志军等人[73]专门研究了非线性功率放大器的非线性失真，通过对信号进行泰勒级数分析，提取指纹特征进行识别；黄渊凌等人[74]通过分析发射机频率源电路的等效数学模型，建立了描述发射机相位噪声特性的自回归-滑动平均(Autoregressive Moving Average Model, ARMA) 模型，并提出通过ARMA参数估计构建辐射源指纹特征，从而完成辐射源个体识别。

随着硬件的发展，特别是器件可编程技术的发展，通过对发射机硬件进行建模分析探求辐射源指纹机理并提取有效特征方法的难度越来越高。

4.2 降维变换特征

在SEI领域，上文中提取的直接测量特征可以直接输入分类器用于辐射源个体识别。由于某些特定原因，例如维度过高或者是表征能力有限等问题，部分直接测量特征需要进行2次提取。2次提取是指在尽可能保持特征原始信息的前提下，进行特征的变换或降维，以便于发掘更深层次更精确的指纹特征，并且易于分类器分类识别。本文将这类特征称为降维变换特征。

降维变换特征本质上是特征分析加工方法，本文主要从两个角度考量：

(1) 高维特征变换，与原始信号结构、初级特征(直接测量特征)密切相关，依据特征分布用简洁的统计特性来表征直接提取的高维度特征，实现特征降维或者特征变换；

(2) 传统特征降维，即直接利用机器学习传统的特征降维方法，利用数学相关实现降维。

常见降维变换特征如表2所示。

4.2.1 高维特征变换

(1) 波形骨架。根据信息不增原理，信号波形本身就是鲁棒性较强的辐射源信号细微特征表征载体。而波形骨架是指最大限度地降低传输信道影响而恢复出辐射源发射出的信号波形。常见的波形骨架提取方法有流形学习——主曲线方法、压缩感知等。

主曲线属于流形学习范畴，指通过数据分布“中央”并满足“自相合”的光滑曲线。形象地说，曲线是数据集合的“骨架”，更能描绘出数据分布的特点，对数据的信息保持性好，如图7所示。用光滑的曲线来代替主成分线来分析数据，求出对称变量之间的光滑曲线，是更加精确的描述实际问题的非线性方法的延伸[75]。

文献[76,77]分别结合非参数化的功率谱和直接双谱对信号进行分析，提取谱线分布的谱骨架，再结合

表 2 基于指纹分析内在逻辑的指纹特征分类框架下的降维变换特征

Tab. 2 Dimensionality reduction feature under feature framework based on the inherent logic of fingerprint feature extraction

特征方法	相关文献
波形骨架	文献[75—78]
分形维数、复杂度	文献[42,79,80]
特定路径积分切片	文献[38,39,81]
熵值计算	文献[59,65,82—84]
奇异值分解等	文献[36,38,85]
传统降维特征	文献[3,86—88]

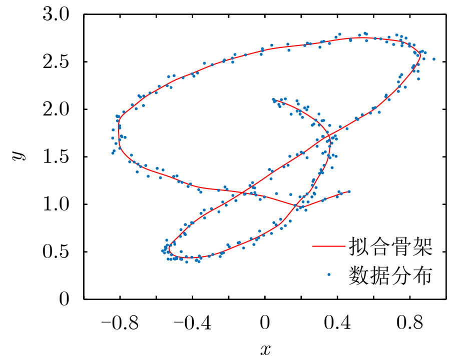


图 7 主曲线提取数据骨架

Fig. 7 Data skeleton extracted by principal curve

多重分形维度描述骨架作为信号指纹特征。然而，很多信号的功率谱和双谱并不适合提取骨架结构，其表示能力在某些情况下并不强，而且会丢失大量信息。

除了上述主曲线方法外，压缩感知[78]也可以用于波形骨架的提取工作。

(2) 分形维数、复杂度。分形是分析非平稳序列的不规则度的有力工具，近年来被广泛应用于非平稳非线性信号处理中。常用于指纹特征提取的分形特征有：信息维数、盒维数、方差维数、Lempel-Ziv复杂度等。桂云川等人[42]在EMD分解基础上计算各个本征模函数(IMF)时域和频域范围内的分形特征结合Hilbert边缘谱上的分形维数与谱对称系数组成特征向量，以此作为最终的辐射源指纹特征；唐智灵等人[79]计算调制无线电信号的方差分形维以及Mandelbrot奇异分形维谱，将信号的调制特征以及非线性变换特征投射到分形特征空间；文献[80]利用盒维数和方差维数表征信号分段后的各个片段，实现个体识别。

(3) 特定路径积分切片。以双谱为例，直接运用双谱矩阵进行特征提取识别需要计算复杂的二维模板，运算效率不高，因而需要通过积分双谱将二维函数转换为一维。特定路径积分按照路径的不同可以分为径向积分双谱(RIB)、轴向积分双谱线(AIB)、圆周积分双谱(CIB)和矩形积分双谱(SIB)等多种[4,81]，如图8所示。

另外，对高维谱图进行切片的思路与特定路径积分类似，但有些切片维度依然较高，还需要进一步的特征降维。循环谱特征的降维方法常采用切片[38,39]。

(4) 熵值计算。简单说，熵值是衡量系统混乱程度的一个指标，在信息论中，又被称为“香农熵”或者“信息熵”。接收到的时间序列经过分解重构后，可以结合熵值计算的基本原理提取降维变换特征。文献[82]提出基于排列熵的辐射源个体特征提取方法，对带有细微差异特征的通信信号进行

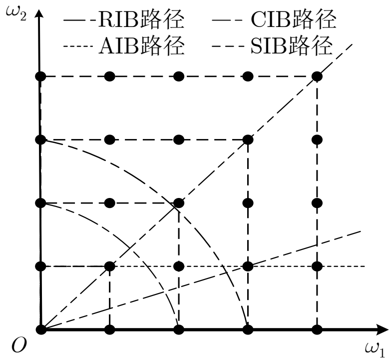


图 8 不同路径积分双谱

Fig. 8 Integral paths of bispectrum

处理，提取刻画原系统细微特征的熵值。除排列熵外，其余熵值算法还有样本熵[59]、能量熵[65]、小波熵[83]、相关熵[84]等。

(5) 奇异值分解等方法。刘婷[38]将循环谱变换得到的矩阵进行奇异值分解，从而提取了更加全面细微的辐射源信号内在特征。也有学者将时频谱变换后的二维全平面信息进行奇异值分解，将特征值特征向量组成指纹特征。Sahmel[85]使用奇异值空间方法研究针对OFDM信号的特定辐射源识别问题；同时，将高维特征转换为图像，把辐射源细微特征的提取识别转换为图像识别问题。

此外，高阶统计量[36]在辐射源个体识别中也可以实现一定的降维效果。

4.2.2 传统特征降维

模式识别中常用的传统降维方法同样能够作为指纹特征2次提取的手段。应用于SEI的降维方法主要有线性判别(Linear Discriminant Analysis, LDA)[86]、主分量分析(Principal Component Analysis, PCA)[3,87,88]等。然而，这类方法没有充分结合指纹特征本身的高度非相关性和非线性等结构特点，也并不能很好的保持原有信息，需要向非线性进行推广。而且将数学相关直接应用于辐射源指纹识别，没有充分考虑信号特征数据的分布情况，存在不少适应性问题。

5 人工智能与辐射源指纹特征提取

近年来，深度学习人工智能(Artificial Intelligence, AI)方法热度不断上升，在图像处理、自然语言理解等领域取得了突破性进展。在辐射源个体识别问题中，AI的加入不仅对识别效果有一定的提升，更影响了原有的经典SEI框架，对分析处理流程进行了新的定义。

早期的相关研究将神经网络作为一种分类器，网络的输入一般为结合专家知识提取的指纹特征，通常情况下是高维特征，网络结构以卷积神经网络(Convolutional Neural Network, CNN)为主。文献[88]将短时傅里叶变换(STFT)时频谱图作为输入；文献[89]利用了降维后的双谱特征；在文献[90]中，作者关注了时频分布的功率值，并且对比了CNN与支持向量机(Support Vector Machine, SVM)，朴素贝叶斯、随机森林、决策树、K近邻(K-Nearest Neighbor, KNN)等传统分类器的分类性能。

后来有研究将特征提取与分类识别两个环节合并在一起，直接输入接收到的原始I/Q复数数据，输出为辐射源识别结果，取得了一定的识别效果[91]。现阶段这种端对端的方法越来越常见[92,93]。

随着神经网络的发展，SEI领域也逐渐出现网络结构改进[93]，对不同的信号样式进行适应性测试等新的研究思路[94,95]。另外，由于深度学习具备强大的学习计算能力等内在的优势，特定场景下的指纹识别问题研究得以开展，比如利用生成对抗网络GAN进行大规模自治组网中非法对抗个体的识别[96]。

然而，深度学习本身可解释性较差，其进行特征提取分析的逻辑类似于黑盒，再加上指纹特征背后对应的机理问题并未完全解决，因此尽管AI方法在识别效果有明显的提高，但是很容易陷入过拟合，面对新数据针对新情景的效果往往不尽如人意。这个瓶颈也限制了基于深度学习的智能指纹识别方法向实际应用系统的转化。

针对此类问题现阶段主要有两种解决思路：

(1) 对原始数据进行数据增强。常见方法有变化训练数据信噪比，调整信号载频等。文献[97]则结合图像的数据扩充技术，通过随机积分方法实现对辐射源指纹识别数据的数据增强；

(2) 结合指纹特征的机理研究。即利用专家知识去掉干扰信息，人为剥离出非硬件电路指纹因素，引导神经网络结构去学习真正的指纹特性。例如美国海军实验室[98]进行载频频偏的估计与去除，降低甚至清除信道环境、参数变化等相关因素的影响，将时域复基带误差信号作为深度CNN网络的输入，在7个Zigbee设备上识别率达到了92.29%。

与以往的端对端方法相比，结合指纹机理来提高基于深度学习的SEI系统性能的思路对信号分析和指纹理解都提出了更高的要求。

6 总结与展望

辐射源个体识别问题经过几十年的发展，研究越来越深入，相关的技术应用也逐步成熟，现阶段传统的辐射源个体识别很大程度上依赖于指纹特征的定义与提取，涉及的特征种类、数量很多，提取分析的角度，依据的理论知识也各不相同。然而，

随着电磁环境日益复杂，相关电子器件制造工艺大幅提高，物理差异日益缩小，提取有效指纹特征的难度越来越大。今后辐射源个体识别技术的相关方法特别是特征方法，仍需要对以下3个方面深入研究：

6.1 智能提取信号特征

智能学习的方法在某种程度上能够摆脱对专家知识的依赖，改变需要人工预定义的传统处理流程，实现自动学习指纹特征，在一定程度上提高特征方法的适应能力。利用AI方法挖掘蕴含在电磁信号中辐射源个体信息，未来一定能在SEI问题上发挥更大的作用。

然而现阶段AI方法智能化、自动化提取指纹特征的工作还处于尝试摸索阶段，特别是如何结合专家经验更好地发挥智能计算的优势，提取真正稳定有效的辐射源指纹特征等问题需要更加细致深入的研究。

6.2 特征方法的综合利用

现有特征的数量种类众多，单一特征的适用范围表征能力有限，不同特征的侧重点关注点存在差异。因此，特征方法的综合利用将从更多的角度刻画辐射源的个体指纹，为SEI问题提供更加全面的信息。

在SEI领域中，特征方法的综合利用，不仅包含模式识别中的多特征融合问题，更强调依赖对信号的理解和认识，发挥不同类别指纹特征对辐射源指纹不同角度刻画能力的优势。既避免冗余，又防止缺漏。例如，在VMD分解后综合时域频域特征[9]；利用决策树进行最优特征组合子集的选择[99]。

针对辐射源指纹问题，未来多特征综合利用的基本思路应当是以提高辐射源指纹特征对不同信号的适应能力，增强对特定信号的针对性，促进原有特征的优势互补为出发点。换句话而言，今后SEI的相关研究应当在定义与提取新特征的同时，提高对原有优异特征的利用。

6.3 特征适应性和扩展性

大部分特征只能适应有限的信号类型，而且其适用范围、适用条件并不明确。当出现新的信号形式时，通常需要结合专家知识进行可用特征的摸索筛选，而面对新的情景原有的识别效果往往大打折扣，甚至失效。如今电磁环境日益复杂，雷达通信乃至物联网设备信号的类型样式不断增多，考验着指纹特征的适应性和扩展性。此外，辐射源指纹特征的边界特性同样值得关注。

随着SEI技术的应用越来越广泛，对指纹特征也提出了越来越高的要求。无论是依赖专家知识人工定义，还是基于AI技术自动学习，未来的SEI技术指纹特征都需要向着更加精细化，智能化，复杂化，更深层次等方向发展。

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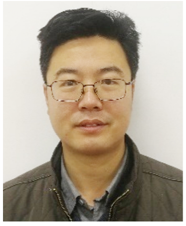

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Overview of Radio Frequency Fingerprint Extraction in Specific Emitter Identification

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Abstract: Specific Emitter Identification (SEI) is a technique of extracting the radio frequency fingerprints of a received electromagnetic signal by only using external feature measurements to determine the specific emitter that transmits the signal. In recent years, the related theories and practical applications of SEI have been continuously improved, and the research on Radio Frequency Fingerprinting (RFF) feature extraction methods has made great progress. Based on domestic and foreign academic achievements, this paper systematically reviews the status quo of the fingerprint feature extraction method of SEI. In addition, a new feature classification framework is proposed based on the inherent logic of fingerprint feature extraction. The classification framework combines the description characteristics of different RFF features and the correlation between them. It divides the existing radio frequency features into two main categories, namely, direct measurement features and dimensionality reduction transform features, which have three levels. Finally, several potential research directions of fingerprint feature extraction are analyzed and explored, aiming to benefit the research and application of SEI.

Key words: Specific Emitter Identification (SEI); Radio frequency fingerprint extraction; Pattern recognition; Signal processing; Feature framework

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1 Introduction

Specific Emitter Identification (SEI), also known as Radio Frequency Fingerprinting (RFF), was first proposed by Northrop Grumman of the United States in the 1960s[1]. It refers to the technology of extracting information reflecting a transmitter's identity (referred to as a "radio frequency fingerprint") by only using the external characteristics of the received signal and comparing the fingerprint information with a database, thereby determining the specific emitter. The fingerprint of an emitter is an inherent characteristic of the hardware of the transmitting device, which is unforgeable, unavoidable, and unchangeable. Moreover, it a weak signal is attached to the transmitting signal in the form of unintentional modulation.

SEI technology has a unique role in identifying specific originating individuals and has attracted widespread attention in the fields of spectrum management, network security, cognitive radio, and electronic countermeasures. Particularly, in military applications, SEI technology can identify specific signals from the complex electromagnetic environment and associate them with individual radiation sources, their platforms and weapon systems, and strategic and tactical targets[1]. It is of great significance for quickly grasping battlefield situations and grasping initiatives during wars.

SEI extracts features containing individual information that characterizes a specific transmitter from the received time series for classification

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and recognition. Therefore, it is essentially a pattern recognition problem.

The structure of a typical SEI system, proposed by Talbot *et al.*[1] in 2003, is presented in Fig. 1. The general processing flow of SEI is as follows: First, the signal is obtained through the radio frequency-receiving subsystem. Second, signal preprocessing is performed, where the received signal is subjected to various processes, such as filtering, denoizing, pulse detection, and signal demodulation. Then, extract the fine features containing the individual information of the radiation source device. Finally, the feature is compared with data in a database and used in classification and recognition algorithms to determine the specific emitter.

In the traditional SEI (different from the deep learning-based intelligent SEI method) system, the definition and extraction of fingerprint features are of significant importance. Therefore, the fingerprint feature extraction of SEI is specifically analyzed in this study.

The structure of this paper is as follows: Section 2 briefly introduces the basic connotation of the fingerprint features of SEI. Section 3 briefly describes the two currently commonly used taxonomies. Section 4 is the main content of this article and proposes a detailed fingerprint feature taxonomy framework. It also presents a detailed review and analysis of the research progress of various fingerprint features under this framework. Section 5 focuses on the current status of Artificial Intelligence (AI) technology applied to SEI. Section 6 summarizes and presents the future prospects of the fingerprint feature extraction of SEI.

2 Fingerprint Features

The imperfection of the emitter hardware chain leads to the inevitable deviation of modulated signals, *i.e.*, it unintentionally modulates the hardware information to the signal within the allowable range of the normal operation of the system. These subtle differences vary from different transmitters, such that the unintentional modulation carries transmitter-specific information. This physical-layer difference is caused by hardware, which is inevitably attached to the intentional modulation and is nearly impossible to mimic, particularly with radio frequency fingerprints.

However, related research on the description and characterization of radio frequency fingerprints is very challenging, mainly due to the following three reasons:

(1) The generation mechanism of radio frequency fingerprints is complex, and the performance is not intuitive and easy to understand like biological fingerprints. It does not have an accurate definition and cannot be accurately modeled and expressed with mathematical tools.

(2) The fingerprint differences caused by hardware between emitters are very subtle, especially for transmitters of the same model and batch of the same manufacturer.

(3) A fingerprint is an unintentional modulation attached to a transmitted signal. Compared with the main part of a signal, its energy is weak and easily affected by many factors, such as complex channel conditions, multipath effects, and environmental noise.

Therefore, SEI needs to extract effective features from as many perspectives as possible to depict real radio frequency fingerprints. These characteristics are called "radio frequency fingerprint features," which should meet the following basic requirements[2–4]:

(1) Universality: The fingerprint features of a

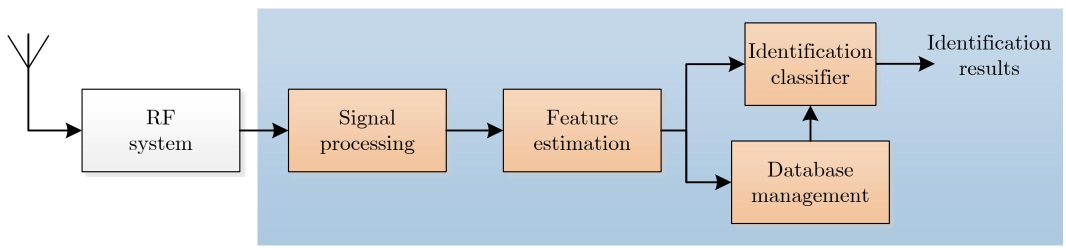


Fig. 1 Structural diagram of typical system for specific emitter identification[1]

transmitter should be universally present in all individual transmitters and all signal samples.

(2) Uniqueness: Feature parameters are different in the samples of different individual transmitters, i.e., the fingerprint features of different emitters are unique, different, and distinguishable.

(3) Stability: The feature of the same individual remains stable or does not change significantly within a certain period of time.

(4) Independence: The individual features of an emitter should be independent of the signal pattern and only related to the transmitter hardware.

(5) Measurability: Feature parameters can be extracted and detected from observed samples using relevant technologies, and the measurement accuracy can meet the requirements of classification.

3 Common Taxonomy of RFF Features

The commonly used taxonomies of fingerprint feature methods for SEI are as follows: Based on the signal type of the analysis object, RFF features can be divided into radar SEI fingerprint features and communication SEI fingerprint features. Based on the signal state of the analysis object, it is divided into transient-state and steady-state features. These taxonomy methods are mainly aimed at the analysis objects of SEI and do not fully consider the performances of features in describing fingerprints and the correlation between different features.

3.1 Radar and communication SEI fingerprint features

Related research on radar signals started in the mid-1960s, and conventional radar parameters were initially used as the identification basis[1], the most typical of which is the use of pulse description words (PDWs) (PDW = {RF, PA, PW, TOA, DOA}) to identify specific radar equipment. As the radar system becomes more complex, the waveform design becomes more complicated, the working frequency band of the radar continues to expand, and the working frequency bands of different radars overlap in a wider range, especially the use of phased-array and agile radars. Therefore, conventional radar parameters can no longer provide enough effective information to meet the corresponding identification requirements[5]. The intra-pulse characteristics of radar signals are increasingly used in SEI.

Compared with radar signals, the research on SEI of communication radiation sources started a little later[6]. SEI of the communication system is also more difficult: communication signal systems are diverse, modulation types are complex and carry a large amount of modulation information, and subtle fingerprint features are usually submerged in the main intentional modulation information. Hence, it is highly difficult to extract fingerprints accurately. Commonly used fingerprint features of communication signals include signal modulation curve-based features and high-dimensional transform domain-based features.

In addition to radar and communication signals in SEI, some studies have focused on other types of signals, such as satellite signals, navigation signals, wireless network signals (*e.g.*, IEEE802.11 series protocol signals), Global System for Mobile communications system signals, electronic tags (Radio Frequency IDentification, RFID), and related radio frequency signals of other Internet of Things devices.

3.2 Transient-state and steady-state features

Based on the inherent manifestations of signal states, *i.e.*, noise, transient, and steady states, fingerprint features can be divided into transient-state and steady-state features.

The transient state refers to the process of equipment switching, mode conversion, symbol conversion of the digital communication system, and external excitation changes in the system. The signals in these processes do not contain any modulated communication data and are only related to the physical-layer characteristics of the device, which can better reflect the unintentional modulation characteristics of emitters[7,8]. The fingerprint features extracted in this process are called transient features.

The premise of transient feature extraction is to accurately obtain complete transient signals. However, the detection of transient signals is relatively complicated, and the main difficulties are as follows. (1)The duration of the transient state is short. (2)Due to noise, the start and end points of the transient state cannot be accurately determined. (3)The amplitude, phase, and frequency characteristics of transient signals are easily affected by nonideal complex channel conditions[9]. Guo *et al.*[10] compared typical transient analysis methods, focusing on the analysis of five transient characteristics, namely, fractal dimension estimation, entropy, energy trajectory, and inherent shape of the rising edge.

A steady-state signal refers to the part of the signal transmitted by the transmitting device after the power is stabilized. The communication signal mainly contains the data part to be transmitted and a small amount of noise. Compared with transient signals, steady-state signals are easier to obtain. When the emitter is working in a stable state, the individual difference caused by numerous hardware units (components or modules) in the physical layer is displayed on the signal in the form of "combined forces", which is stable. However, the state fingerprint features are hidden deep in the modulated signal and noise, making it difficult to extract.

4 Feature Framework based on the Inherent Logic of the Fingerprint Analysis

Considering the inherent logic of fingerprint feature extraction in SEI, this study combined the mathematical principles of feature tools based on the feature extraction method, proposed a new fingerprint feature framework, and divided the existing fingerprint features into two categories, namely, direct measurement features (primary features) and dimensionality reduction transformation features (secondary features). Moreover, combined with the principle of the fingerprint feature analysis, each category is classified in more detail. The features are divided into three levels for SEI.

The direct measurement feature refers to the feature directly extracted from the received signal based on the basic signal analysis process (*e.g.*, basic parameter information and basic transformation information). Under normal circumstances, the input for calculating direct measurement features can only be the preprocessed signal series. The results can be directly used as a fingerprint feature for SEI. Features with higher dimensionality can also be further subjected to secondary feature transformation, and the final result after the calculation (*i.e.*, dimensionality reduction transformation feature) is used as the fingerprint feature.

The dimensionality reduction transformation feature is not closely integrated with the signal characteristics and does not rely on the basic knowledge of electromagnetic signal analysis. However, these features are usually considered feature description methods to optimize the direct measurement features. *i.e.*, on the basis of the primary features, the secondary features are extracted based on a certain mathematical transformation. In special cases, it can also be used directly to extract the features of the original signal.

To facilitate understanding and discussion, let $x(n)$ denote the preprocessed data, $F_1\{\cdot\}$ be the direct measurement feature calculation, $F_2\{\cdot\}$ be the dimensionality reduction transformation feature extraction, and $y(m)$ denotes the final fingerprint feature result, i.e., the input of the classifier. The extracted fingerprint features are

$$y_1(m_1) = F_1\{x(n)\}, \quad m_1 = 1, 2, \cdots, M_1 \tag{1}$$

$$y_2(m_2) = F_2\{F_1\{x(n)\}\}, \quad m_2 = 1, 2, \cdots, M_2 \tag{2}$$

where y_1 and y_2 represent the direct measurement feature and dimensionality reduction transformation, respectively, and M_1, $M_2 (M_2 \leq M_1)$ is the corresponding feature dimension. However, in theory, it is also possible to directly extract the dimensionality reduction transform characteristics of a signal, *i.e.*, $y_2(m_2) = F_2\{x(n)\}$. For example, the fractal dimension estimation of the original signal can be directly used for SEI. In practical applications, this situation is relatively rare, and it usually needs to meet certain prerequisites, such as a specific signal pattern or specific processing. In the taxonomy proposed in this paper, such features that rely on the special structure of the signal and the basic signal analysis methods are classified as direct measurement features. Thus, in a strict sense, the above situation can be expressed by Eq. (2). In short, in this taxonomy, $F_1\{\cdot\}$, $F_2\{\cdot\}$ are serial, usually first $F_1\{\cdot\}$ and then comes $F_2\{\cdot\}$. $F_2\{\cdot\}$ can be omitted in some cases.

Compared with the current methods, the framework refines the classification of fingerprint features, and it is consistent with the inherent logic of fingerprint feature processing and analysis. In addition, it covers all commonly used fingerprint features at this stage and minimizes the overlap of feature methods as much as possible. Hence, researchers should further refine and improve the features and study their combinations.

The following is a detailed analysis of the classification framework and development status of fingerprint features under various categories. In the taxonomy framework based on the inherent logic of the fingerprint analysis, the two major categories of features are shown in Tab. 1 and 2. Tab. 1 shows the direct measurement feature, and Tab. 2 shows the dimensionality reduction transformation feature.

4.1 Direct measurement feature

The direct measurement feature refers to the fingerprint feature that is closely related to the common basic signal analysis methods. This type of feature directly acts on the preprocessed signal to obtain or retain as much of the original signal's fingerprint information as possible. This study mainly considers the following aspects of the direct measurement fingerprint features of SEI:

Tab. 1 Direct measurement features under the feature framework based on the inherent logic of fingerprint feature extraction

Feature method		Reference
Basic parameter information	General parameter	[1,11,12]
	Envelope feature	[13–18]
	Instantaneous feature	[19–23]
	Modulation parameter	[24–26]
	Spectrum feature	[3–27]
Basic transformation information	Time-frequency analysis	[28–32]
	High-order spectrum	[33–37]
	Cyclic spectrum	[38,39]
	Hilbert spectrum	[40–43]
Signal special structure	Signal preamble	[23,44,45]
	Radar signal analysis	[46–51]
Decomposition and reconstruction information	EMD	[42,43,52–55]
	ITD	[56–63]
	VMD	[9,43,64,65]
	Phase space analysis	[2,66–69]
	Segmentation reconstruction	[70,71]
Transmitter hardware characteristics	Equivalent circuit model	[72]
	Nonlinear circuit model	[73]
	Frequency source circuit	[74]

Basic parameter information: commonly used communication signal parameters, radar signal parameters, time-domain and frequency-domain basic parameter information, and other parameters that can be used to identify individual information in the conventional signal processing process;

Basic transformation information: basic signal transformation, including time-frequency transformation, high-order spectrum analysis, and cyclic spectrum analysis;

Signal special structure: specific structures contained in the transmitted signal, such as the IEEE802.11 series protocol signal frame header and handshake signal in digital radio transmission, which are used to meet specific communication requirements or corresponding standards;

Decomposition and reconstruction information: corresponding transformations of the received time series to improve the data dimension, including adaptive signal decomposition methods and phase space reconstruction methods;

Transmitter hardware characteristics: the fingerprint feature generation mechanism modeling analysis carried out according to the nonideal characteristics of the related hardware in the signal transmission process.

4.1.1 Basic parameter information

Basic parameter information refers to the conventional parameters of the signal, such as the conventional parameters of the radar signal (*e.g.*, PDW); envelope shape; rising edge time; intrapulse characteristics, including Instantaneous Frequency (IF) and Instantaneous Phase (IP); symbol rate of the communication signal; carrier frequency deviation; spectral characteristics; modulation parameters; and modulation domain errors (including IQ imbalance and constellation offset). Such features are mainly concentrated in the time and frequency domains and are common in various signal processing procedures. Compared with other signal processing processes, SEI usually requires high accuracy for estimating such parameters.

Fingerprint features based on the basic parameter information are divided into five categories in this paper: conventional parameters, envelope characteristics, instantaneous parameters, modulation errors, and spectral distribution characteristics. The following describes their applications in SEI.

(1) General parameter

The SEI technology based on the features of conventional radar parameters mainly relies on the features directly measured or estimated by the signal measurement and detection systems[1,11], such as carrier frequency, pulse azimuth, pulse coding method, pulse width, pulse arrival time, and pulse amplitude. Then, these features are compared with the known signal parameters in the database to obtain relevant information about the intercepted pulse signal[12]. The early radar system was relatively simple, the electromagnetic signal density was small, the pulse signal frequency domain span was small and less overlapped, the signal form was simple, and the parameters were relatively stable, so the corresponding signal identification based on the conventional parameters was effective before. Nowadays, as the electromagnetic environment is becoming increasingly complex, the signal is diversified, and the difference in signal parameters is constantly shrinking. Thus, it is difficult to accurately confirm the specific emitter using conventional parameters directly as fingerprint features.

(2) Envelope feature

Due to the nonideality of the electronic device itself, there is inevitably a slight difference in transmitter performance. This subtle difference can be mapped on the shape of the signal's time-domain pulse envelope, so the waveform is accompanied by the characteristics of a specific transmitter, which can be used as a basis for individual identification. The pulse envelope waveform of the radar signal is shown in Fig. 2.

The received signal can be affected by the multipath effect, transmitter phase noise, and additive noise, and its pulse envelope will produce varying degrees of distortion and fading[13]. When the influence of the multipath effect is large, the pulse envelope shape may even change. Studies have found that the rising edge of the pulse envelope is the least affected by the multipath among the envelope parameters. Therefore, the front edge of the envelope (including the rising edge and part of the pulse top waveform) is often used as the fingerprint feature of the radiation source[14,15].

In Ref. [16], the wavelet transform technology for the envelope analysis was combined, and high-precision envelope information was extracted as the fingerprint feature of SEI. In Ref. [14], Liu Xu et al. combined the recurrence rate analysis method to detect the start and end points of a signal and defined three new variables, namely, fitting rising angle, fitting falling angle, and P/S, to describe the envelope shape of pulses. In Ref. [15], two envelope features R and J excavated the spurious characteristics of the spurious modulation of the signal envelope to a certain extent. Rehman *et al.*[17] used the short-time Fourier transform spectrogram to detect the transient energy envelope curve of the Bluetooth signal and extracted the area under the normalized curve, duration of the transient, kurtosis, skewness, and variance of the curve to describe the subtle characteristics of the envelope. In Ref. [18], four envelope features, namely, Linear Envelope (LE), Tangent Envelope (TE), Quadratic Envelope (QE), and Sigmoid function Envelope (SE), were defined.

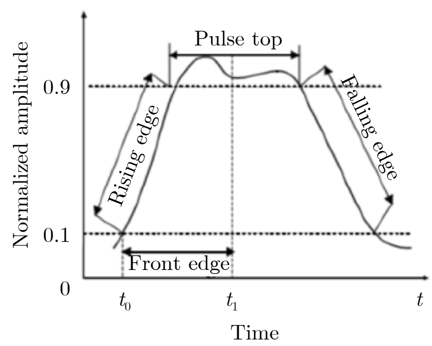


Fig. 2 Radar pulse envelope

Particularly, the radar pulse waveform is susceptible to atmospheric propagation effects, making incidental amplitude modulation an unreliable parameter.

(3) Instantaneous feature

Instantaneous features include IF, IP, and Instantaneous Amplitude (IA). The estimation methods of the instantaneous parameters mainly include the Hilbert Transform (HT), energy separation, generalized zero crossings, empirical Amplitude Modulated (AM)-Frequency Modulated (FM) decomposition, direct quadrature, and normalized HT[19]. Among them, the HT is the most commonly used.

The transient features are mainly used in the transient state of the signal and the frame header structure (preamble) of specific signals. The changes in amplitude, phase, and frequency of the processes often become different over time. Fig. 3 shows the IF features of secondary response signals when four civil aviation aircraft communicate with the ground. Hall *et al.*[20] extracted a number of features from the IF, IP, and IA of the transient state, including the standard deviation of normalized instantaneous features, variance of change in amplitude, standard deviation of normalized I/Q data, power per section, and average change in DWT coefficients. In Ref. [21], the five-dimensional feature vector was defined based on the IA, which effectively realizes the identification of wireless network cards and Bluetooth devices. Huang *et al.*[22] specifically addressed the problem of individual identification of Frequency-Shift Keying (FSK) radio stations, completed the estimation of FSK frequency distortion parameters, and established the basis of the IF fingerprint model. In Ref. [23], an envelope and IP were combined to extract the individual characteristics of radar signals, and the influence of the radar operating mode on device-specific features was analyzed based on measured data.

(4) Modulation parameter

The fingerprint feature based on the modulation domain error is also called the constellation shape error fingerprint feature. It is a steady-state fingerprint feature (*i.e.*, PAssive RAdiometric Device Identification System, PARADIS) proposed by Brik *et al.*[24] in 2008. This method takes into account the influence of various nonideal characteristics of a device on the modulation sig-

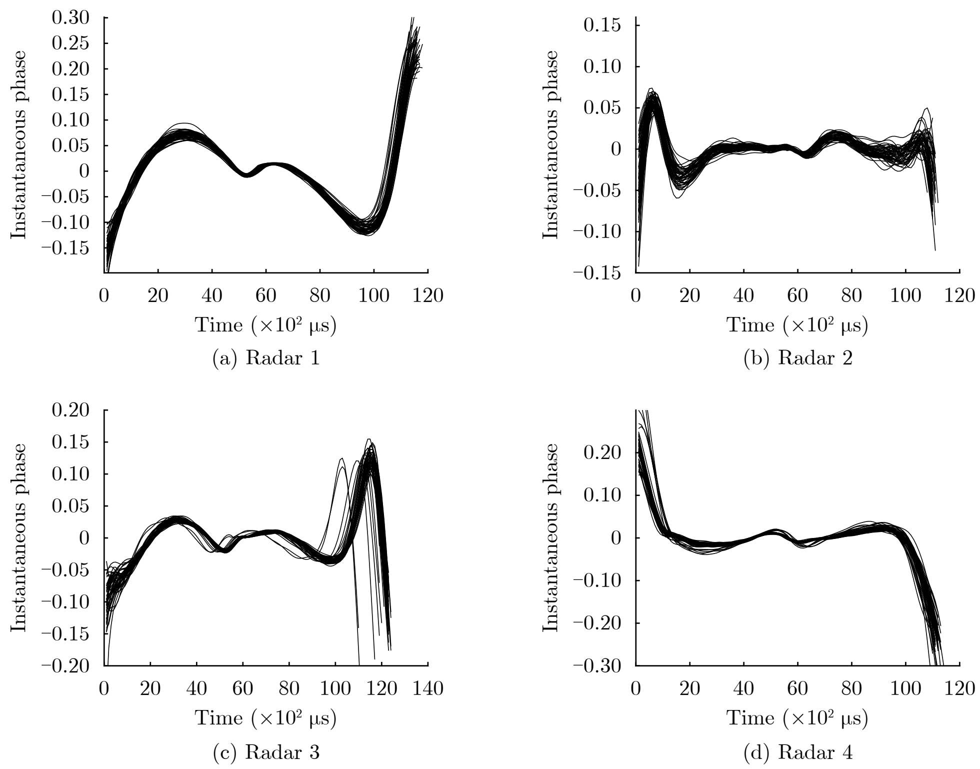


Fig. 3 Instantaneous phase characteristics of the secondary response signals of four civil aviation aircrafts

nal, including the I/Q channel offset, frequency offset, and limiting effect on the amplitude, which usually appear as constellation deterioration in the modulation domain. The nonlinear characteristics of the oscillator source, mixer, power amplifier, and other devices in different radiation source hardware devices are slightly different. Therefore, the shape of the signal constellation diagram is different. Based on the differences in the constellation diagram shape, we can determine the radiation source where the signal comes from.

Brik *et al.*[24] compared the difference in the distribution of scattered points on the constellation diagram; defined fingerprint features, such as phase error, amplitude error, and I/Q channel offset; and successfully realized the identification of 138 wireless network cards (quadrature phase shift keying modulation). In Refs. [25,26], further research was performed on the modulation domain error based on the work of Brik *et al.*[24]. The former extracts constellation diagrams on the basis of carrier recovery, symbol rate estimation, and timing estimation and uses the Hausdorff distance to measure the similarity of transmitters. The latter analyzes the influence of phase noise on the modulation domain, dynamically clusters the observation points of the received signal, obtains a reconstructed constellation, and completes the classification of the constellation according to the maximum likelihood criterion.

The fingerprint feature based on the constellation error gets rid of the dependence on the signal time-domain waveform, suppresses the influence of noise and bad channel effect to a certain extent, and is easily implemented in the hardware. However, its shortcomings are also prominent. First, it is only applicable to digital modulation signals. Second, it is necessary to accurately estimate information, such as frequency, code rate, and modulation pattern, and the recognition effect largely depends on the results of the digital demodulation.

(5) Spectrum feature

The reference frequency of the signal generated by the individual crystal oscillators of different emitters is different, which causes the difference between the carrier frequency and the code rate of the signal, and the relative deviation (the ratio of the deviation to the standard deviation) has nothing to do with the standard deviation. In Ref. [3], the accurate estimation of the carrier frequency and code rate was examined, and the effectiveness of frequency deviation as a fingerprint feature to identify specific emitters was verified.

Although the relative deviation between the carrier frequency and the code rate is distinguishable, the implementation of SEI requires an extremely high estimation accuracy, and it is difficult to obtain the standard value of the signal parameter in practical applications. Thus, it is impossible to obtain an accurate relative deviation for SEI.

In addition, the asymmetric characteristics of the spectrum can be used as fingerprint features to identify individual radiation sources[27].

4.1.2 Basic transformation information

On the basis of basic parameters, transform-domain information, such as time-frequency spectrum, high-order spectrum, and Hilbert spectrum, have recently been widely used for RFF.

(1) Time-frequency analysis

Time-frequency analysis, particularly Joint Time-Frequency Analysis (JTFA), provides joint distribution information of the time and frequency domains. It clearly describes the relationship between the signal frequency and time and is a powerful tool for analyzing time-varying nonstationary signals. The most common time-frequency analysis methods include the Short-Time Fourier Transform (STFT), wavelet transform, Wegener distribution, and quadratic time-frequency distribution.

Fingerprint features based on STFT were analyzed in Ref. [28]. In Ref. [29], the time–frequency characteristics of binary signals were systematically analyzed. In Ref. [30], the wavelet transform was used to extract the unintentional modulation of RFID. In Ref. [31], transmitter identification methods based on the wavelet transform were systematically analyzed. In Ref. [32], the improved Choi-Williams Distribution

(CWD) of Wigner-Ville distribution was introduced, the CWD was used to convert the one-dimensional (1D) time-domain signal to a two-dimensional (2D) time-frequency domain image, and the modulation information was extracted in the time-frequency plane.

Such fingerprint features are often limited by the inherent drawbacks of time-frequency tools and face a series of problems. For example, (1)STFT has shortcomings in solving nonlinear problems. (2)A contradiction exists between the choice of window function and its length and the resolution of the spectrogram. (3)The wavelet transform method relies on the choice of wavelet packet and has low precision and poor adaptability. (4)There are serious cross terms in quadratic time-frequency analysis methods, and the energy of the entire time-frequency plane may appear negative.

(2) High-order spectrum

Actual signals do not strictly obey the Gaussian distribution, and the signals emitted by different emitters show non-Gaussian characteristics. A high-order spectrum, like the Fourier transform of high-order cumulants, is an effective non-Gaussian analysis tool. The high-order spectrum does not affect the time, can retain the signal amplitude and phase information, and suppress the Gaussian noise. Among them, the third-order spectrum, also known as the bispectrum, with the characteristics of a time-shift invariance, scale variability, and phase retention, is the most widely used in SEI. Fig. 4 shows the bispectrum feature distribution of two FM radio signals, which indicates that there are significant differences in the bispectrum features of signals from different radiation sources.

The bispectrum feature is a third-order statistical feature with a relatively large complexity, and the unique information of the transmitter is scattered in a high-dimensional space, making classification and recognition difficult. Therefore, when utilizing high-order spectrum features, the dimensionality reduction transform algorithms, such as representative slice integration, should be combined, and the dimensionality reduction feature based on the distribution of high-dimensional data should be extracted.

In Refs. [33–37], high-order spectra were chosen as the preliminary high-dimensional features, and different mathematical tools were used to extract the secondary features. In Ref. [3], Locally Linear Embedding (LLE) manifold reduction was used to perform a dimensionality reduction analysis on high-dimensional Square Integral Bispectra (SIB) features and improves the distance definition of LLE samples and output dimension estimation method for SEI.

(3) Cyclic spectrum

Cyclo-stationarity is an important characteristic of a modulated signal. The cyclic spectral density function contains information, such as frequency and phase related to the modulated signal. Cyclic spectrum analysis can distinguish the signal from the noise with non-cyclic stationery. Therefore, the anti-interference, signal analysis, and characterization ability of the cyclic spectrum analysis are stronger than those of the

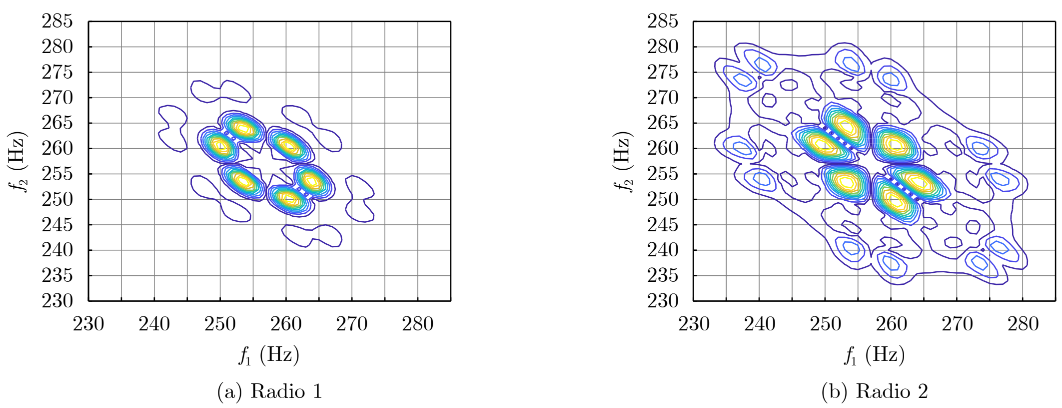


Fig. 4 Bispectrum characteristic images of two FM radio signal

power spectrum[38]. The most commonly used non-parametric cyclic spectrum estimation methods are the time-domain and frequency-domain smooth periodogram methods.

In Ref. [39], the α cross-sectional spectrum (cyclic spectrum slice) of the cyclic spectrum density $f = 0$ was chosen as the initial high-dimensional feature, and the cyclic spectrum difference in the signal was analyzed to achieve the purpose of SEI.

(4) Hilbert spectrum

The Hilbert spectrum is derived from the Hilbert-Huang Transform (HHT). Intrinsic Mode Functions (IMFs) can be obtained after the Empirical Mode Decomposition (EMD) of the signal is subjected to the HT. After the HT, the relationship among time, frequency, and amplitude of the IMF can be obtained. The distribution of amplitude on the time-frequency plane is the Hilbert spectrum $H(t,\omega)$.

Wang *et al.*[40] used the improved HHT algorithm to calculate the signal Hilbert spectrum . Wang Li[41] summarized some of the fingerprint features that can be extracted on the basis of the HHT. In Ref. [42], the Hilbert edge spectrum was extracted. In Ref. [43], the performance of the HHT fingerprint features in a single-hop scenario and relaying scenario and in different channels was paid attention to.

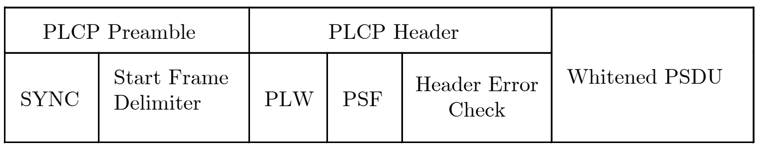
4.1.3 Signal special structure

Some signals have unique structural characteristics and can be used for SEI, such as the preamble of the wireless signal under the 802.11 protocols, and its format is shown in Fig. 5. Under the same standard, the preamble contains the same content, which can avoid the impact of different modulation information, is more robust than other features, and is suitable for the identification of different wireless network devices.

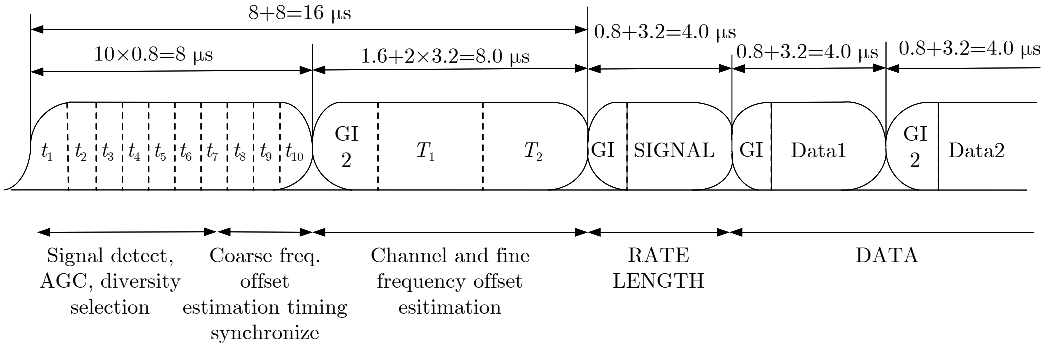
In Refs. [23,44], a Wi-Fi signal preamble was used to identify wireless network cards. In Ref. [45], seven software radio peripheral transmitters (Universal Software Radio Peripheral, USRP) were combined with the signal generated by the protocol simulation to identify emitters.

However, most types of signals do not have a preamble, and in the case of non-cooperation, it is usually impossible to obtain a complete data frame header.

Similar to the preamble, radar signals also have special structures or parameters that can be used for identification, such as the Ambiguity Function (AF) and Doppler[46]. Among them, the AF was first used for radar analysis and waveform design, and now it is also often used to characterize the individual differences of different signals. In Ref. [47], radar signal sorting was performed by extracting the main ridge slice of the



(a) Preamble frame format



(b) Synchronization (SYNC) structure of preamble

Fig. 5 Preamble format of standard IEEE802.11b ambiguity function. In Ref. [48], the local AF slice was defined, and its fast estimation algorithm was proposed on the basis of the method in Ref. [47] to extract and identify different radar pulse data. Wang Lei *et al.*[49–51] further optimized the fingerprinting features of the AF .

4.1.4 Decomposition and reconstruction information

SEI does not focus on the main information conveyed in the signal transmission process, but it pays attention to details other than the main components of the signal. Using decomposition and reconstruction algorithms to improve the original signal dimension, fingerprint-related features can be extracted from a higher level, and at the same time, a new idea for separating the main component and secondary component (spurious component) of the signal can be provided.

Commonly used decomposition methods include EMD, Intrinsic Time-scale Decomposition (ITD), and Variational Mode Decomposition (VMD). Reconstruction methods include phase space reconstruction and segmentation reconstruction.

Decomposition and reconstruction make the data have higher dimensions, more variables, and more complex forms. Therefore, understanding the differences and connections between different signal components in a high-dimensional space and extracting the truly meaningful information are the keys to use such features to realize SEI. Otherwise, mapping data to high-dimensional space can only result in greater computational pressure and information redundancy.

(1) EMD

EMD was first proposed by Norden *et al.*[52] in 1998, which is a posterior adaptive time-frequency analysis method for nonlinear and nonstationary signals.

The basic calculation method of EMD is to use the tertiary spline interpolation method to continuously and iteratively search for the upper and lower envelopes of the local maximum and minimum points of the original signal, obtain the IMF components, and complete the decomposition process. Fig. 6 shows the time-domain waveforms of a signal and all the decomposed IMFs after EMD. The first layer of the sub-pictures is the original signal waveform, and the remaining sub-pictures correspond to each IMF. The figure shows that EMD basically works according to the frequency from high to low. The first few layers of IMF components with high frequency and low amplitude can be roughly understood as high-frequency spurious components attached to the signal.

In the past 20 years, there have been many SEI-related studies based on EMD at home and abroad. In Ref. [53], EMD was first used for SEI and compared with wavelet decomposition. In Ref. [54], IMF was used to reconstruct signals to obtain stable time-frequency distribution characteristics. Liang *et al.*[55] used EMD to separate the main components and spurious components containing individual information about the radiation source. In Ref. [42], the fractal features of IMF in the time and frequency domains were extracted, combining IF and Hilbert edge spectrum as fingerprint features. In Ref. [43], three different features based on EMD were proposed, and its performance was explored for the first time in the relay scene.

(2) ITD

In 2007, Frei M G *et al.*[56] proposed ITD, which decomposes a signal into the sum of several inherent rotation components and a monotonic trend. Compared with EMD, the process of filtering and interpolation is subtracted.

In Ref. [57], the instantaneous parameters of ITD were used to reconstruct the time spectrum, and the spectral symmetry deviation coefficient of the signal spectrum was defined as a feature. In Ref. [58], the fractal features, RJ features, and edge spectrum features of different rotation components after ITD were extracted. In Ref. [59], ITD was combined with the nonlinear analysis method, the correlation coefficient was used to filter out the appropriate signal components, and the entropy data of each layer of the signal were extracted. Ren *et al.*[60] combined ITD and image processing methods to extract corresponding fingerprint features. In addition, ITD has a wide range of applications in the fields of the biologic-

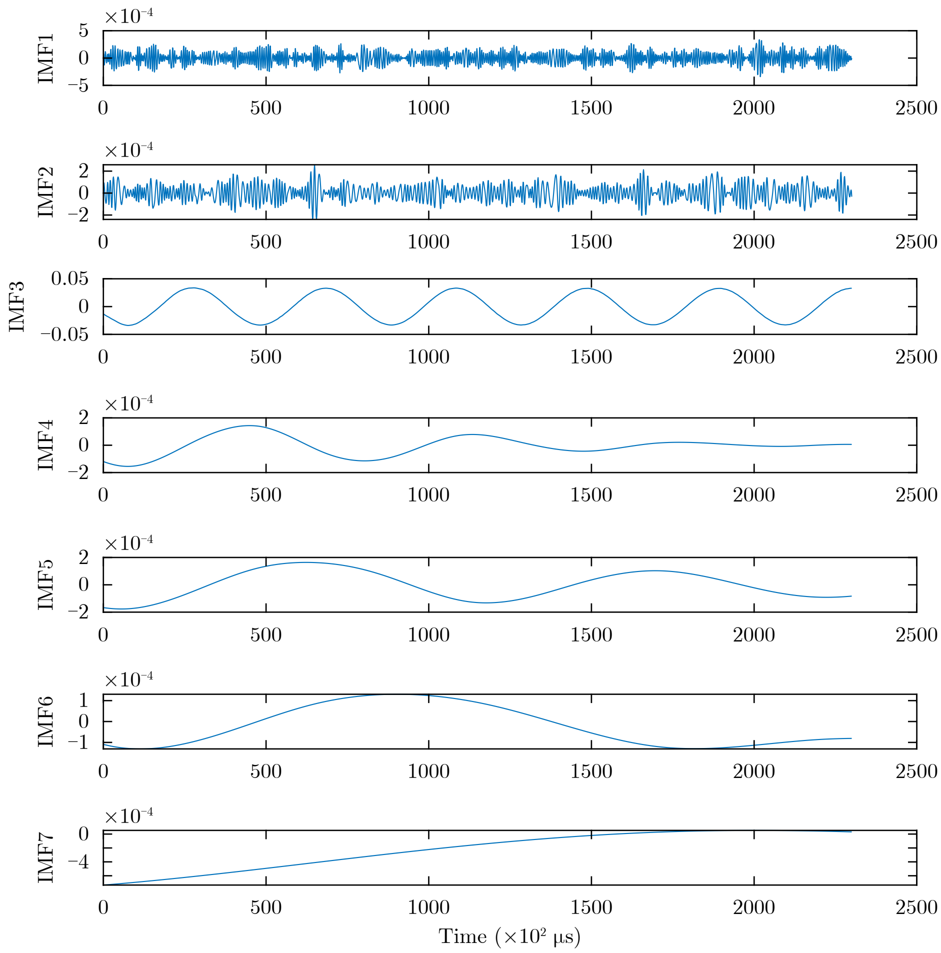


Fig. 6 Schematic of empirical mode decomposition results

al signal[61], fault diagnosis[62], and system detection[61,63].

(3) VMD

VMD was proposed by Dragomiretskiy *et al.*[64] in 2014. It is a non-recursive adaptive quasi-orthogonal signal decomposition method in the time and frequency domains. It plays an important role in the nonlinear signal analysis[65]. The VMD method has stable decomposition results with simple calculations and no modal aliasing problems. The decomposed basic component IMF has the characteristics of AM–FM modulated narrowband signals, and its IF has a practical physical meaning, which has natural advantages for SEI. Satija *et al.*[9] applied VMD to fingerprint recognition based on the method proposed in Ref. [43] and constructed VMD entropy (VMD-Entropy) and cumulant (VMD-EM^2) as fingerprint features.

(4) Signal reconstruction

The received signal can be understood as a 1D time series formed by high-dimensional data projections carrying transmission information and emitter-specific fingerprint information. Therefore, the reconstruction of the signal can also be called ascending-dimensional restoration. Common reconstruction methods include phase space reconstruction based on nonlinear signal characteristics, segmentation reconstruction, and parameter imaging.

The phase space analysis is one of the basic analysis methods of nonlinear dynamics. Each phase point in the phase space corresponds to a state of the dynamic system, and the change in the phase point corresponds to the state evolution of the system. The use of a time series to construct a phase space equivalent to the original phase space of the system, i.e., phase space reconstruction, is the first step to analyze the nonlinearity of the time series[66].

Theoretically, different transmitters correspond to different nonlinear systems, and there must be hardware fingerprint characteristics inherent to the specific transmitter in the reconstructed phase space. Carrol[67] first used the phase space reconstruction method to solve the SEI problem. Xu Dan[2], Yuan Yingjun[68], and Zhu Shengli[69] discussed in detail the application of phase space theory to SEI in their doctoral dissertations.

In addition to phase space reconstruction, domestic and foreign scholars have also tried other segmentation reconstruction methods. For example, T. J. Bihl *et al.*[70] proposed a signal segmentation and feature vector combination method based on a sliding window function. Zhu[71] reconstructed a time series into a Horizontal Visibility Graph (HVG).

4.1.5 Transmitter hardware characteristics

The analysis of the fingerprint mechanism is an important research content of SEI, which is of great significance for exploring the physical nature of signal fingerprint features and extracting effective fingerprint features.

In Ref. [72], the hardware structure of transmitters was first introduced, the equivalent circuit model of the radio frequency oscillator for the transmitter with a free-running oscillator was constructed, and a modeled SEI technology was proposed. When the modulation voltage greatly changes, this method can make up for the shortcomings of traditional methods in measuring the rising- and falling-edge delays. Xu Zhijun *et al.*[73] specifically studied the nonlinear distortion of nonlinear power amplifiers by performing a Taylor series analysis on the signal. Huang Yuanling *et al.*[74] analyzed the equivalent Mathematical model of the transmitter frequency source circuit and established an Autoregressive Moving Average (ARMA) model to describe the phase noise characteristics of a transmitter. They proposed to construct the fingerprint characteristics of the radiation source through the ARMA parameter estimation, thereby completing SEI.

With the development of hardware, particularly the development of programmable device technology, the exploration of a fingerprint mechanism of a radiation source and extraction of an effective feature method by modeling and analyzing the transmitter hardware have become increasingly difficult.

4.2 Dimensionality reduction transformation

In the SEI field, the direct measurement features extracted above can be directly inputted to the classifier for identification. However, due to some specific reasons, such as high dimensionality and limited characterization capabilities, some direct measurement features need to be further purified into the secondary feature. Secondary feature extraction refers to feature transformation or dimensionality reduction on the premise of keeping the original information of the feature as much as possible, exploring deeper and more accurate fingerprint features, and facilitating easy classification or recognition by the classifier. In this paper, this type of secondary feature is also called the dimensionality reduction transform feature.

The dimensionality reduction transformation feature is essentially a feature analysis and processing method, which is mainly considered from two perspectives in this paper:

(1) High-dimensional feature transformation: This involves secondary features that are closely related to the original signal structure and primary features (direct measurement features). Statistical tools are commonly used to characterize directly extracted high-dimensional features to achieve feature dimensionality reduction or feature transformation according to the feature distribution.

(2) Traditional feature dimensionality reduction: The traditional dimensionality reduction method of machine learning is directly used, and the mathematical correlation is used to achieve dimensionality reduction.

Parts of the dimensionality reduction transformation features are shown in Tab. 2.

4.2.1 High-dimensional feature transformation

(1) Waveform skeleton

According to the principle of non-increasing information in signal processing, the signal waveform itself is the carrier of the subtle features of a radiator signal that is more robust and contains the most information. The waveform skeleton method aims to minimize the influence of the transmission channel and restore the signal waveform emitted by the emitter, which includes the manifold learning-master curve method and compressed sensing.

The master curve belongs to the category of manifold learning, which refers to a smooth curve that passes through the center of the data distribution and satisfies self-consistency. This curve is the skeleton of the data collection, which can better describe the characteristics of the data distribution and retain the information of the data, as shown in Fig. 7. Using a smooth curve instead of the principal component line to analyze the data and finding the smooth curve between the symmetrical variables is an extension of the nonlinear method that more accurately describes the actual problem[75].

In Refs. [76,77], the signal was analyzed by combining the non-parametric power spectrum and direct bispectrum, extract the spectrum skeleton of the spectral line distribution, and then combine the multifractal dimension to describe the skeleton as the signal fingerprint feature.

Tab. 2 Dimensionality reduction feature under feature framework based on the inherent logic of fingerprint feature extraction

Feature Method	Reference
Waveform skeleton	[75–78]
Fractal and complexity	[42,79,80]
Specific path integration/slicing	[38,39,81]
Entropy	[59,65,82–84]
SVD	[36,38,85]
Traditional dimensionality reduction	[3,86–88]

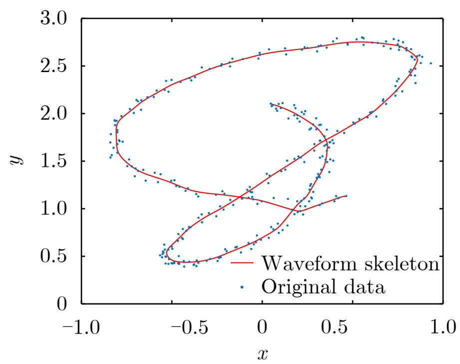


Fig. 7 Data skeleton extracted by principal curve

However, the power spectrum and bispectrum of many signals are not suitable for extracting the skeleton structure, and their representation ability is not strong in some cases. Hence, a lot of information will be lost.

In addition to the above-mentioned master curve method, compressed sensing[78] can also be used to extract the waveform skeleton.

(2) Fractal and complexity

A fractal is a powerful tool used to analyze the irregularity of non-stationary series and has been widely used in non-stationary and nonlinear signal processing in recent years. Fractal features commonly used in fingerprint feature extraction are the information dimension, box dimension, variance dimension, and Lempel–Ziv complexity. Gui Yunchuan *et al.*[42] calculated the fractal features of eigenmode functions (*i.e.*, IMF) in the time and frequency domains on the basis of the EMD, combined with the fractal dimension on the Hilbert edge spectrum and spectral symmetry coefficient to form the feature vector. Tang *et al.*[79] calculated the variance fractal dimension of a modulated radio signal and the Mandelbrot singular fractal dimension spectrum and projected the modulation feature and nonlinear transformation feature of the signal to the fractal feature space. In Ref. [80], the box dimension and variance dimension were used to characterize each segment of the signal segmentation to realize SEI.

(3) Specific path integration/slicing

Taking a bispectrum as an example, the direct use of a bispectrum matrix for feature extraction and recognition requires the calculation of complex 2D templates, and the computational efficiency is relatively low. Therefore, it is necessary to convert the 2D function into 1D by integrating the bispectrum. Specific path integrals can be divided into the Radial Integral Bispectrum (RIB), Axial Integral Bispectrum (AIB), Circular Integral Bispectrum (CIB), and SIB according to different paths[4,81], as shown in Fig. 8.

In addition, the idea of slicing high-dimensional spectrograms is similar to that of specific path integration, but some slices are still high in dimensionality. Hence, further feature dimension-

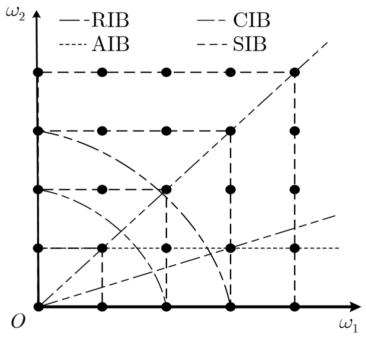


Fig. 8 Integral paths of bispectrum

ality reduction is needed. The dimensionality reduction method of cyclic spectrum features often uses slices[38,39].

(4) Entropy

Entropy is an indicator that measures the degree of chaos in a system. In information theory, it is also called Shannon entropy or information entropy. After the received time series is decomposed and reconstructed, the dimensionality reduction transformation feature can be extracted in combination with the basic principle of entropy calculation. In Ref. [82], a method for extracting the individual characteristics of emitters based on the permutation entropy of communication signals was proposed, and entropies that characterize the subtle features of an original system were extracted. In addition to permutation entropy, other entropy algorithms include sample entropy[59], energy entropy[65], wavelet entropy[83], and correlation entropy[84].

(5) Singular value decomposition

Liu Ting[38] performed singular value decomposition (SVD) on a matrix obtained via the cyclic spectrum transformation, which extracted comprehensive and subtle inherent characteristics of a radiation source signal. Some scholars also performed SVD of 2D full-plane information after time–frequency spectrum transformation and then combined the eigenvalue and eigenvectors into a fingerprint feature. Sahmel[85] used the singular value space method to study the identification of SEI for OFDM signals. They also converted high-dimensional features into images and converted the extraction and identification of subtle features of radiation sources into image recognition problems.

In addition, high-order statistics[36] can achieve a certain dimensionality reduction effect in SEI.

4.2.2 Traditional dimensionality reduction

The traditional dimensionality reduction methods in pattern recognition can also be used as a means of extracting secondary fingerprint features, which mainly include linear discriminant analysis[86] and principal component analysis[3,87,88]. However, this kind of method does not fully integrate the structural characteristics of fingerprint features, such as a high degree of non-correlation and nonlinearity, and cannot maintain the original information well. Moreover, the direct application of mathematical correlation to SEI ignores the distribution characteristics of features, and there are many adaptability problems.

5 AI and Fingerprint Feature Extraction

In recent years, the popularity of deep learning AI methods has continued to rise, and breakthroughs have been made in the fields of image processing and natural language understanding. Regarding the identification of individual radiation sources, the addition of AI not only improves the identification effect to a certain extent but also affects the original classic SEI framework and redefines the analysis and processing process.

Early related research tended to use neural networks as a classifier. The input of the network is generally fingerprint features extracted with expert knowledge, usually high-dimensional features, and the network structure is mainly a Convolutional Neural Network (CNN). In Ref. [88], an STFT time spectrogram was taken as an input. In Ref. [89], the bispectrum feature was used after dimensionality reduction. In Ref. [90], the author considered the energy of the time-frequency distribution and compared the CNN’s classification performance with those of traditional classifiers, such as Support Vector Machines (SVM), naive Bayes, random forests, decision trees, and K-nearest neighbors).

Later, some studies have merged two links, namely, feature extraction and classification recognition, directly inputted the received original

I/Q complex data, and outputted radiation source recognition results, which achieved a certain recognition effect[91]. At this stage, the end-to-end approach has become increasingly common[92,93].

With the development of neural networks, new research ideas, such as network structure improvements and adaptive testing of different signal styles, have gradually appeared in the SEI field[93–95]. In addition, due to the inherent advantages of deep learning, such as strong learning and computing capabilities, research on fingerprint recognition in specific scenarios can be performed, such as the use of a generative adversarial network, to identify illegally confronted devices in large-scale autonomous networks[96].

However, deep learning itself is poor in interpretability. Its feature extraction and analysis logic are similar to a black box. In addition, the corresponding mechanism behind fingerprint features has not been completely solved. Therefore, although the AI method has significantly improved the recognition effect, the possibility of overfitting is still large, and its performance in new data and new scenarios is often unsatisfactory. This bottleneck also limits the transformation of fingerprint identification methods based on deep learning to practical application systems.

At this stage, two main solutions for such problems are proposed:

(1) Data enhancement of original data

Common methods include changing the signal-to-noise ratio of the training data and adjusting the signal carrier frequency. In Ref. [97], inspired by the image data enhancement technology, the data enhancement of SEI through the random integration method was realized.

(2) Research combining the mechanism of fingerprint features

Expert knowledge can be used to remove interference information, artificially strip out non-hardware circuit fingerprint factors, and guide the neural network to learn real fingerprint features. For example, in Ref. [98], the carrier frequency offset was estimated and removed; the influence of the channel environment, parameter changes, and other related factors were reduced or eliminated; and finally, the time-domain complex baseband error signal was obtained as the input of the deep CNN network. The recognition rate reached 92.29%.

Compared with the previous end-to-end methods, the idea of combining fingerprint mechanisms to improve the performance of SEI systems based on deep learning puts forward higher requirements for signal analysis and fingerprint understanding.

6 Conclusions and Outlooks

After decades of development, the issue in SEI has become more profound, and related technology applications have gradually matured. Nowadays, traditional SEI largely relies on the definition and extraction of fingerprint features. Many types and numbers of features are involved, and the angles of extraction and analysis and the theoretical knowledge based on them are also different. However, as the electromagnetic environment is becoming increasingly complex, the manufacturing process of related electronic devices has been greatly improved, and the physical differences have been shrinking, making it more difficult to extract effective fingerprint features. In the future, the related methods of SEI technology, especially the feature extraction method, still need in-depth research on the following three aspects:

6.1 Intelligent extraction of signal features

Deep learning-based SEI methods can get rid of the dependence on expert knowledge, change the traditional processing procedures that require manual pre-definition, realize automatic learning of fingerprint features, and improve the adaptability of feature methods to a certain extent. Using AI methods to mine the individual information of radiation sources contained in electromagnetic signals will certainly play a great role in SEI issues in the future.

However, at this stage, the intelligent and automatic fingerprint feature extraction is still in the trial and exploration stage. In particular, how to combine expert experience, make better use of the advantages of intelligent computing, and extract the truly stable and effective fingerprint features of the radiation source, among other issues, require more detailed and in-depth research.

6.2 Comprehensive utilization of multiple features

There are many types of existing features, the scope of application of a single feature is limited, and the advantages of different features are different. Therefore, comprehensive utilization of features will characterize the radio frequency fingerprints of emitters from other angles and provide more comprehensive information for SEI.

In the field of SEI, the comprehensive utilization of feature methods not only includes the traditional problem of multi-feature fusion in pattern recognition but also emphasizes the dependence on the understanding of signals and aims to combine the advantages of different types of fingerprint features in the ability to describe the fingerprint from different angles. We need to avoid useless redundancy and prevent the omission of information. For example, the time- and frequency-domain features were integrated after VMD decomposition in Ref. [9], while the decision tree was used to select the optimal feature combination subset in Ref. [99].

Aiming at the problem of SEI, the basic idea of the comprehensive utilization of multiple features in the future should be to improve the adaptability of fingerprint features to different signals, enhance the pertinence of specific signals, and promote the complementary advantages of original features. In other words, future SEI-related research should improve the use of original excellent features while defining and extracting new features.

6.3 Adaptability and scalability

Most features can only be adapted to limited signal types, and their scope and conditions of applications are unclear. When a new signal form appears, it is usually necessary to combine expert knowledge to explore and screen the available features. In addition, the original recognition effect in the face of a new situation is often greatly compromised or even invalid. The electromagnetic environment is becoming increasingly complex, and the types and patterns of signals are increasing, which changes the adaptability and scalability of fingerprint features. In addition, the boundary characteristics of the fingerprint feature of SEI are worthy of attention.

As the application of SEI technology becomes increasingly extensive, growing requirements are put forward for fingerprint features. Whether it is manually defined by expert knowledge or automatic learning based on AI technology, the fingerprint features of SEI technology in the future will need to be developed in a more refined, intelligent, complex, and in-depth direction.

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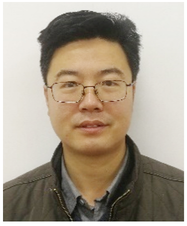

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