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基于小波散射网络的聚乙烯管道热熔接头缺陷 太赫兹识别

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摘 要:采用频率范围为 0.25~2.5 THz 的反射式脉冲太赫兹时域光谱系统,对聚乙烯管道热熔接头缺陷进行了无损检测。利用 PE100 板材之间的热熔焊接模拟实际聚乙烯管道的热熔焊接,分别制作了标准热熔焊接和冷焊、过焊、未熔合和夹杂热熔缺陷接头样件。通过太赫兹系统逐点扫描,并对接头位置进行了波形及峰度成像分析。其中未熔合和夹杂热熔缺陷样件与标准焊接样件在波形上有明显差别;冷焊、过焊、未熔合及夹杂热熔缺陷在峰度成像图中可见明显缺陷轮廓。针对标准焊接和夹杂、未熔合热熔缺陷构建第一类小波散射网络-卷积神经网络缺陷识别模型进行缺陷定性分析,其缺陷识别率均可达到 98% 以上。针对标准焊接和夹杂金属、粗沙、树枝缺陷构建第二类缺陷识别模型进行定量识别,其缺陷识别相对误差均在 7.42% 以下。

关键词:太赫兹;无损检测;聚乙烯热熔接头;小波散射网络;缺陷识别

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0 引言

聚乙烯(Polyethylene, PE)管道因在耐腐蚀性、可塑性及性价比等方面优势明显,成为燃气和石油管道领域的首选。燃气、石油因易燃易爆等特点极易产生安全隐患,因此在生产和使用中要严格控制质量。PE 管道在铺设时通常在现场进行焊接,焊接过程中的人为因素、长期使用的风化、腐蚀影响等均可能导致管道焊接接头出现缺陷,因此对焊接管道接头质量检测尤为重要^[1-2]。目前对热熔接头的检测手段主要为超声波检测、红外热成像检测、射线检测等。ALESHIN N P 等^[3]对 PE 管道热熔焊接接头进行了超声波检测。通过使用弦式传感器的超声波检测夹杂类固体缺陷相对于 X 射线的可靠性为 90%,对未融合等半透明缺陷的可靠性降低到 70%~80%。朱志彬^[4]提出了基于持续激励双面透射检测的 PE 管道热熔接头红外热成像检测方法,通过有限元模拟与试验研究结合的方法,证实了红外检测热像序列图可以有效地识别出孔洞缺陷的位置和大小。邵翔等^[5]对夹杂、未熔合等人工缺陷的 PE 管道热熔和电熔焊接接头进行射线检测,发现对于体积型缺陷的检出率高,而对于面积型缺陷较难检出。

太赫兹(Terahertz, THz)无损检测技术^[6]作为一种无损、非电离、非接触的新型检测技术,对非极性、非金属材料具有很强的穿透力。基于 THz 成像技术的无损检测技术能够获得被测样件的频域、时域和空间信息,能对材料的缺陷进行清晰成像,具有很高的缺陷检测及定位能力,在无损检测领域^[7]的优势也逐渐凸显,可以作为传统检测技术的有效补充。JANSEN C 等^[8]利用太赫兹时域光谱技术(Terahertz Time Domain Spectroscopy, THz-TDS)对两层 PE 材料间的粘接质量及金属、沙子等夹杂缺陷进行了检测。陈强等^[9]基于

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THz-TDS对PE管道接头的老化及磨痕、分层、夹杂缺陷进行检测,实验结果表明随着老化时间延长,材料的吸收系数随着老化时间的增加而明显下降。PALKA N等^[10]通过X射线和THz波对超高分子量PE复合材料分层缺陷进行了无损成像,确定了分层的分布和腔体的尺寸,并通过飞行时间分析和信号处理,实现了样品的三维成像,与X射线成像结果一致。

为解决PE管道热熔接头的冷焊、过焊、未熔合以及夹杂缺陷检测的问题,采用反射式脉冲太赫兹时域光谱技术对PE热熔接头进行检测,通过对不同缺陷THz检测信号的分析及成像,设计小波散射网络-卷积神经网络缺陷识别模型,实现对热熔焊接缺陷的准确识别。

1 样品制备及太赫兹检测

1.1 样品制备

PE管道热熔焊接^[11]是利用加热工具将管道与管道端面或与管件端面加热到指定温度,在规定压力下持续一定时间,使两端面熔合形成符合质量要求的热熔焊接接头。

常见缺陷种类^[12]主要分为:1)夹杂:管材焊接后残留在焊缝的异物;2)未熔合:管材与管材之间未完全熔化结合;3)过焊:表现为卷边过大,主要是焊接过程中加热板加热时间过长或温度过高。4)冷焊:主要是管材吸热时间较短接头部分未达到完全熔化,或焊接压力过低不能有效连接两端面。

选用规格为40 mm×80 mm×20 mm的白色PE100板材来模拟制作PE管道热熔焊接缺陷试件。所选材料级别和厚度的标准热熔焊接工艺参数为焊接温度210℃;焊接压力1.0 MPa;允许切换(延迟)时间≤6 s。根据常见缺陷种类,通过调节焊接温度及时间、预埋金属和沙石等、设计不同焊接面积来制作冷焊、过焊、夹杂和未熔合热熔接头缺陷样件。焊接过程如图1,首先将板材固定至夹具相应位置,加热板放入两板材待加热端面并且加压,控制加热时间使待焊接端面加热至熔融状态,然后抽出加热板后迅速贴合端面,并保持压力一定时间冷却,即可形成符合焊接质量要求的热熔焊接接头。最后通过铣削、打磨等平面处理形成待检测样件。

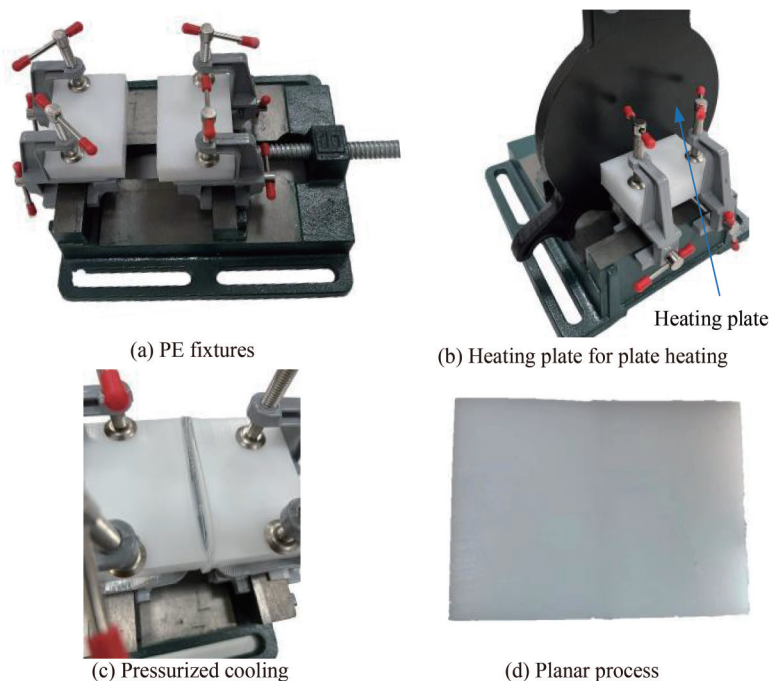


图1 聚乙烯板材实际热熔焊接过程

Fig. 1 Actual hot melting welding process of polyethylene sheet

1.2 检测系统

图2为所搭建的THz-TDS^[13-14]系统,选用的激光器为光纤飞秒激光器,重复频率为80 MHz,脉冲中心波长为1 550 nm,脉冲宽度为100 fs。其发射的激光脉冲通过分束镜被分为泵浦光、探测光,经过泵浦光入

射至 THz 发射元件上产生 THz 脉冲;通过光电导取样测量可以促使探测光获取到时间分辨 THz 光谱信息。将经过平面处理的聚乙烯热熔接头样件固定在与 THz 镜头垂直的样品台,通过设置二维扫描平台中 x - y 的移动顺序和速度对其焊缝部分进行逐点扫描。为提高接头缺陷识别的精度将 x - y 方向的扫描步距均设置为 0.3 mm,由于样件厚度为 20 mm,为使样件的上下表面反射回波都收入时间窗口将扫描范围调整为 320 ps。在实际的 PE 管道的检测中只需将管道固定至旋转轴上,将 THz 探测器固定至线性模组上,通过旋转轴和移动轨道的联动使 THz 探测器垂直于管道进行逐点扫描即可获得 PE 管道的 THz 光谱信号^[15],如图 3。针对管道在线检测可采用机器人搭载太赫兹探测器^[16]对其进行扫描检测,将管道的三维模型导入机器人系统中,机器人对其进行路径规划后进行太赫兹逐点扫描。

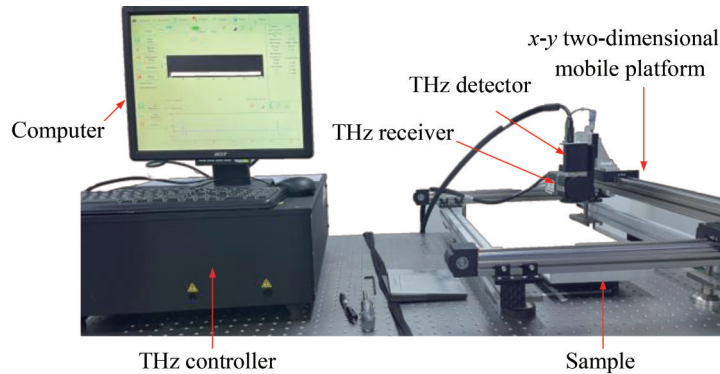


图 2 太赫兹时域光谱系统实物
Fig.2 Physical of THz-TDS system

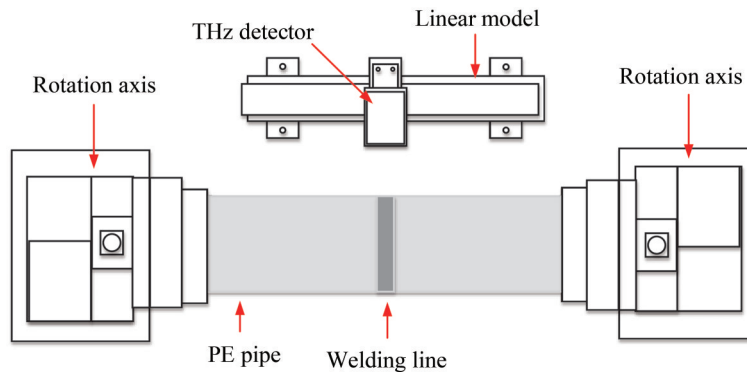


图 3 聚乙烯管道太赫兹检测模拟图
Fig.3 THz detection simulation diagram of polyethylene pipe

2 特征分析

2.1 太赫兹波形分析

图 4 为不同缺陷样件的 THz 波形对比图,在 50~60 ps 区间内的反射回波为 THz 波通过空气层到 PE 材料上表面的反射信号,在 260~270 ps 内的反射回波为 THz 波通过 PE 材料到金属板的反射信号。图 4(a)为冷焊、过焊缺陷样件与标准焊接样件的波形对比图。由于冷焊和过焊缺陷样件都是与标准焊接样件相同厚度的 PE 单种材料,其两端面的 PE 分子交织程度不同,所以波形上几乎无差别。图 4(b)为未熔合缺陷样件与标准焊接样件的波形对比图,由于未熔合缺陷样件在焊缝中存在不规则的缝隙使得检测波形在 260~270 ps 区间内的反射强度略低。图 4(c)为夹杂金属、夹杂粗沙和夹杂树枝三类夹杂缺陷样件与标准焊接样件的波形对比图,在 100~120 ps 区间可以看到 THz 传播到夹杂的金属后的反射回波,在夹杂粗沙和树枝的样件中则没有看到夹杂物的反射回波,在 260~270 ps 能明显看到三类夹杂缺陷样件下表面反射信号强度都有大幅度减少。这主要是由于夹杂类的缺陷体积相对较小,且形状不规则,导致部分反射的 THz 波无法被接收器接收以及太赫兹波的衍射效应。

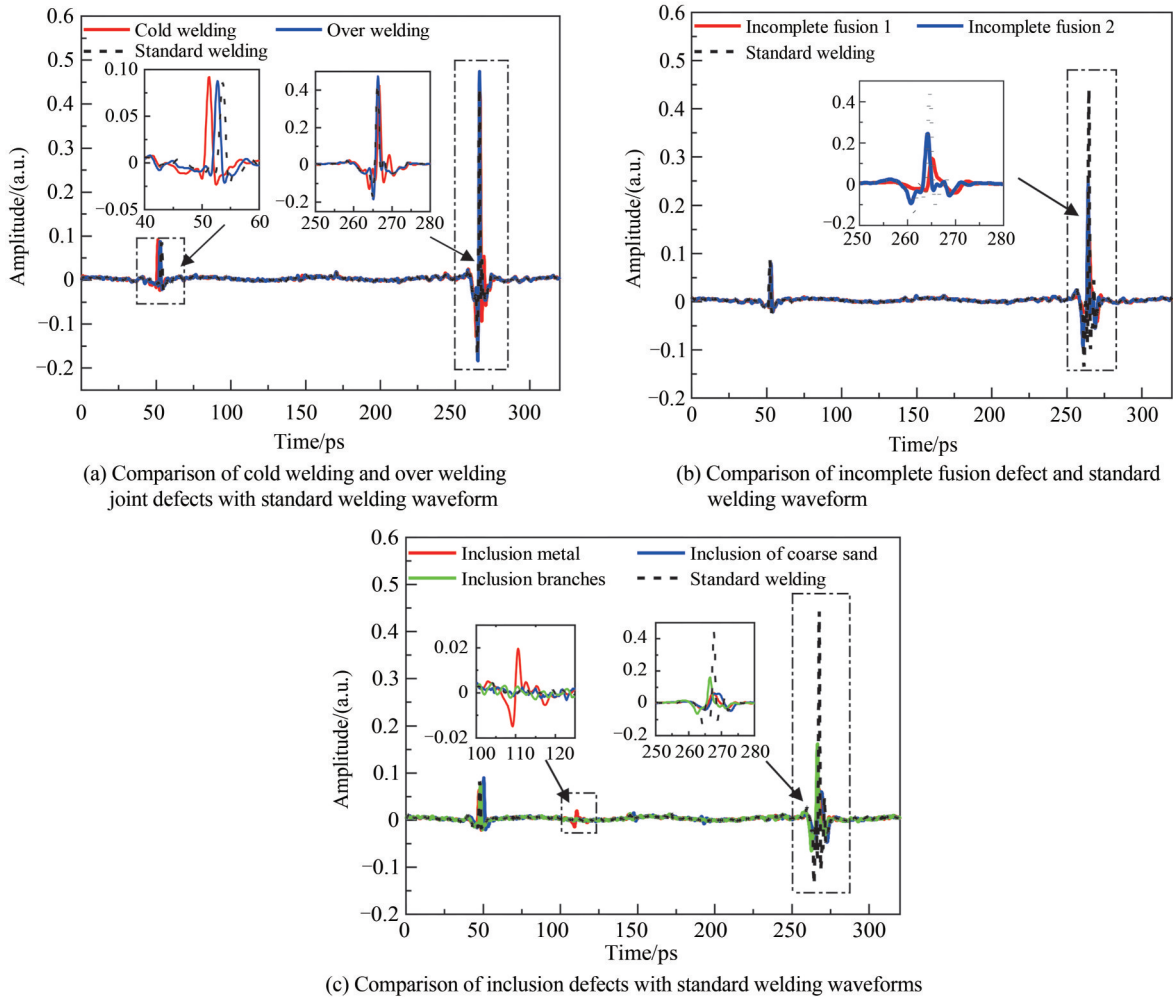


图4 THz波形对比

Fig.4 THz detection waveform comparison

2.2 太赫兹成像分析

采用标准热熔焊接工艺参数制作标准焊接样件;只改变焊接温度至 250°C ,制作过焊缺陷样件;只改变焊接温度至 150°C ,制作冷焊缺陷样件。图5为标准焊接与过焊、冷焊缺陷样件焊接后未经过平面处理和经过平面处理后对应的THz峰度成像图。

由于冷焊、标准焊接、过焊焊接焊缝处的卷边程度依次减少,从图5(a)~(c)中的卷边程度能明显分辨其缺陷种类。从THz峰度成像图可以看出标准焊接样件接头处有一条明显且连续无波动的焊缝,计算其焊缝宽度约为 3.9 mm 。过焊和冷焊缺陷样件的焊缝宽度均较宽且不规则,在焊缝处均有多处明显的焊接缺陷。

分别选择待熔合面带有 $5\text{ mm}\times 40\text{ mm}$ 和 $3\text{ mm}\times 35\text{ mm}$ 的凹槽来制作因焊接面积不同而形成的未熔合缺陷样件。图6为未熔合样件焊接前实物图和经过焊接、平面处理后对应的THz峰度成像图。从成像图能清楚看到未熔合缺陷部分的轮廓与实物图中凹槽部分高度吻合。

分别在焊缝中预埋金属1、金属2、树枝、粗沙的接头样件,图7为夹杂缺陷样件预埋实物图和经过焊接、平面处理后对应的THz峰度成像图。从成像图中能清楚看到夹杂物的轮廓,其缺陷成像与夹杂实物相一致,且在图7(e)~(g)中标记部分为检测出的非预制缺陷^[17]。在焊接过程中由于加入夹杂物使得切换时间过长,导致熔合面部分可能产生未熔合或冷焊缺陷。

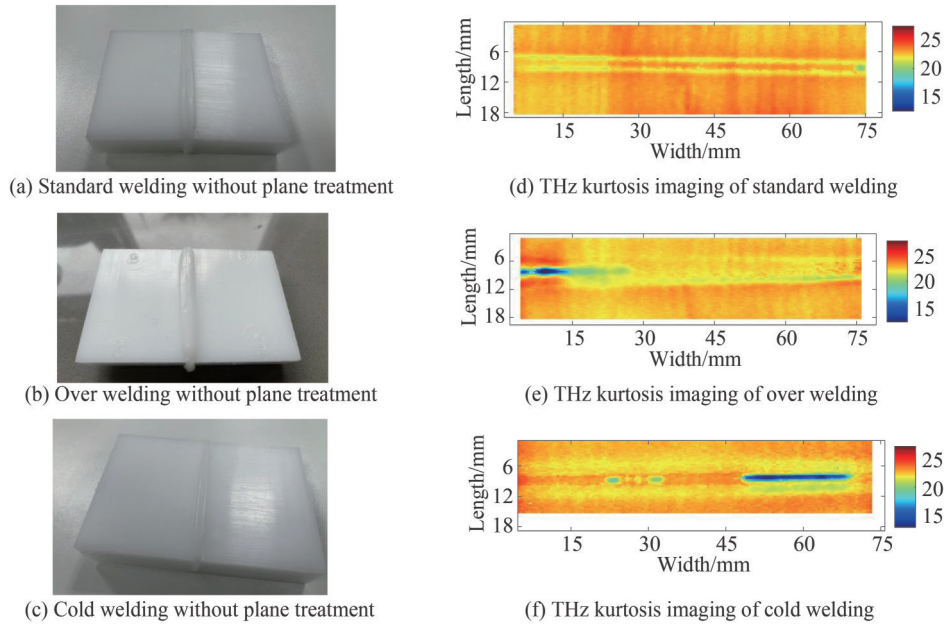


图5 样品热熔焊接后未经过平面处理图和对应的THz峰度成像图

Fig.5 The sample has not undergone planar processing and corresponding THz kurtosis imaging after hot fusion welding

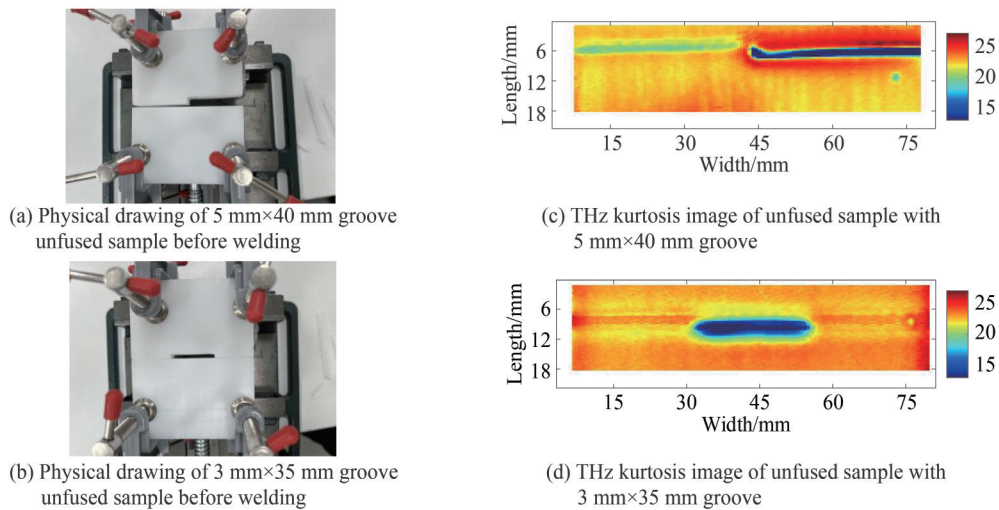
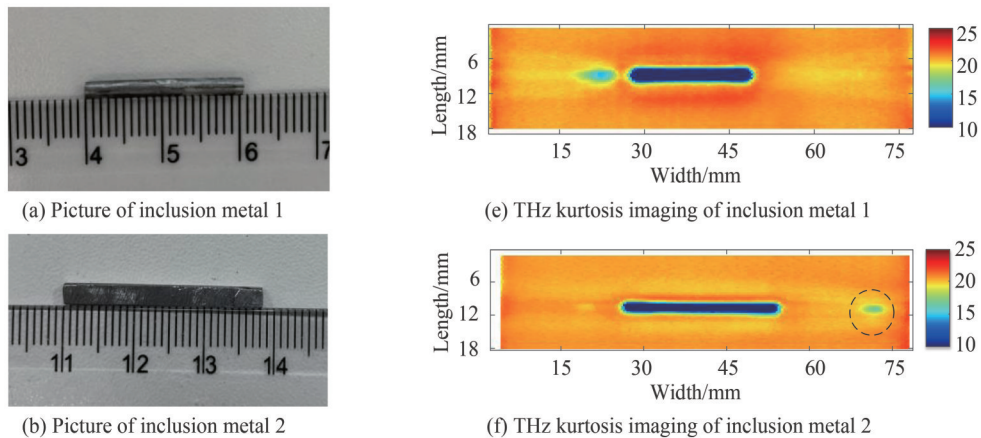


图6 未熔合缺陷样品焊接前实物图和对应的太赫兹检测峰度成像图

Fig.6 The incomplete fusion sample before welding and the corresponding THz detection kurtosis imaging diagram



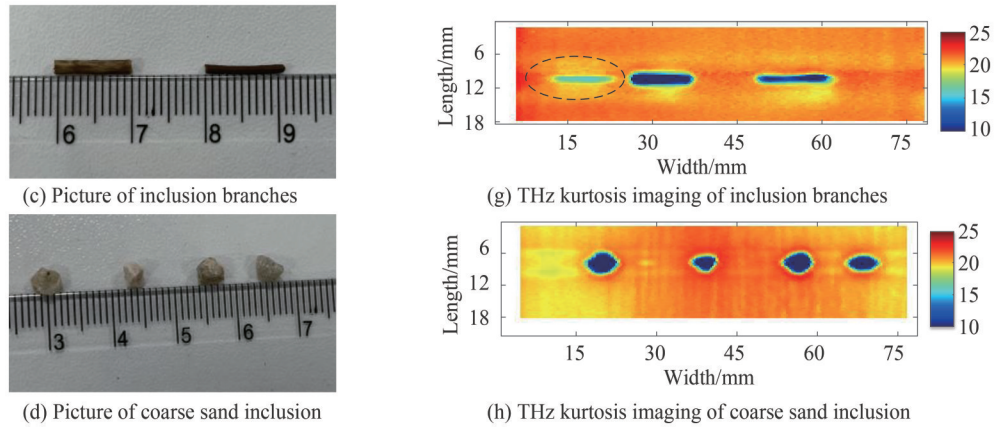


图7 夹杂缺陷样品预埋实物图和对应的THz峰度成像图

Fig.7 The embedded object of inclusion defect sample and the corresponding THz kurtosis imaging are required

3 缺陷识别

为了精确识别PE热熔焊接缺陷的种类和大小,构建了小波散射网络-卷积神经网络缺陷识别模型。通过对每种缺陷制作10个缺陷样品并每类样本均随机选取3000组数据来组成数据集,用于对识别模型进行训练与测试,最后将上述热熔接头样品THz波形数据通过小波散射特征提取导入CNN识别模型中进行分类识别输出。

图8为其流程图:1)小波散射网络特征提取。对THz原始波形数据进行分割降维,将降维后波形数据

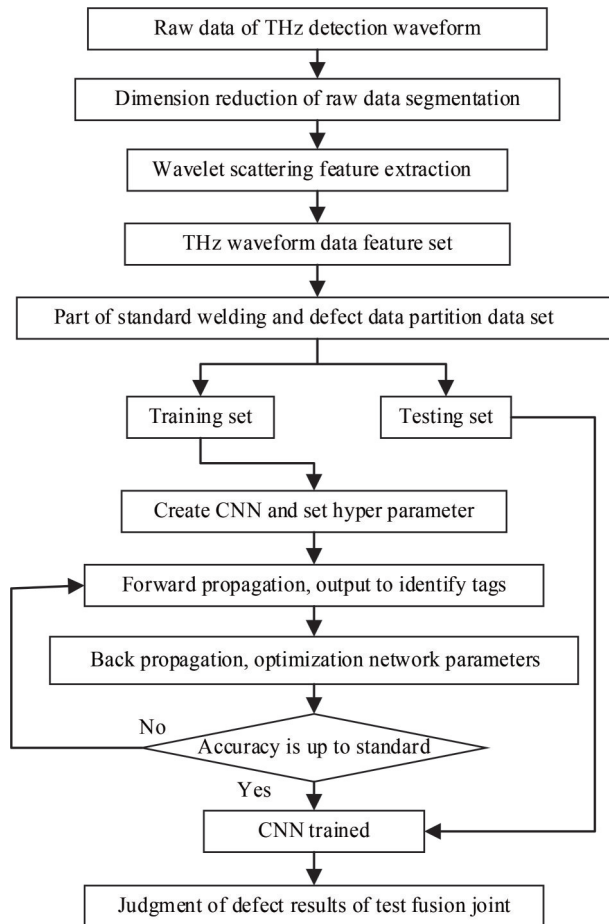


图8 基于小波散射网络-卷积神经网络缺陷分类流程

Fig.8 Defect classification flow based on wavelet scattering network-convolutional neural network

通过小波散射网络进行特征提取并重塑成一个 4-D 数组,用于卷积神经网络(Convolutional Neural Network,CNN)模型输入。2)CNN模型。将数据集划分为训练集和测试集,当准确度达到要求后停止训练输出每个迭代的准确度和损失图,保存网络参数。3)测试模型。在测试集上测试训练好的 CNN 模型,输出测试结果的混淆矩阵。

3.1 小波散射网络特征提取

小波散射变换^[18-20]是使用深度卷积网络实现的,该网络迭代传统的小波变换、非线性和平均算子。设 $f(t)$ 为要分析的信号,用低通滤波器 ϕ 和小波函数 ψ 来构造覆盖信号所包含的全部频率的滤波器, $\phi_j(t)$ 为低通滤波器在尺度 T 上提供 f 局部平移不变特征, Λ_k 表示倍频分辨率,多尺度高通滤波器 $\{\psi_{j_k}\}_{j_k \in \Lambda_k}$ 由小波函数 ψ 构造,散射系数为 S_k 。卷积 $S_0 f(t) = f * \phi_j(t)$ 生成在尺度 T 上的局部平移不变特征 f ,但也会导致高频信息的丢失。这些丢失的高频 W_1 可以通过小波模变换来恢复,可表示为

$$|W_1|f = \{S_0 f(t), |f * \phi_{j_1}(t)|\} \quad j_1 \in \Lambda_1 \quad (1)$$

一阶散射系数通过 ϕ_j 平均小波模系数获得

$$S_1 f(t) = \{|f * \phi_{j_1}| * \phi_j(t)\} \quad j_1 \in \Lambda_1 \quad (2)$$

恢复通过平均丢失的信息, $S_1 f(t)$ 可以看作是低频分量 $|f * \phi_{j_1}|$, 可以通过式(3)提取互补的高频系数 W_2 , 可表示为

$$|W_2| |f * \phi_{j_1}| = \{S_1 f(t), ||f * \phi_{j_1}| * \phi_{j_2}(t)||\} \quad j_2 \in \Lambda_2 \quad (3)$$

进一步定义了二阶散射系数 S_2 , 表示为

$$S_2 f(t) = \{||f * \phi_{j_1}| * \phi_{j_2}| \phi_j(t)\} \quad j_i \in \Lambda_i \quad i = 1, 2 \quad (4)$$

迭代上述过程定义了小波模卷积, 表示为

$$U_m f(t) = \{||f * \phi_{j_1}| * \dots * \phi_{j_m}\} \quad j_i \in \Lambda_i \quad i = 1, 2, \dots, m \quad (5)$$

分别对 $U_m f(t)$ 和 ϕ_j 取平均得出 m 阶散射系数为

$$S_m f(t) = \{|||f * \phi_{j_1}| * \dots * \phi_{j_m}| \phi_j(t)\} \quad j_i \in \Lambda_i \quad i = 1, 2, \dots, m \quad (6)$$

该散射过程如图 9。最终的散射矩阵特征表示为

$$Sf(t) = \{S_m f(t)\} \quad 0 \leq m \leq l \quad (7)$$

聚合所有阶的散射系数来描述输入 THz 检测信号的小波散射特征, 其中 l 是最大分解阶。本次实验设

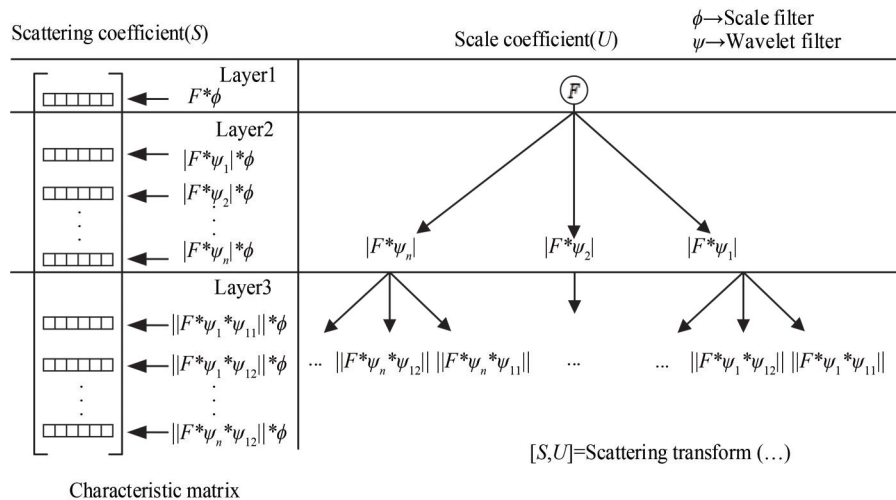


图9 小波散射框架

Fig.9 Wavelet scattering framework

置小波散射网络参数为:信号长度设为最大数组长度即 THz 时域信号长度 701,过采样因子设为 1,信号扩展法选值为 reflection。

3.2 卷积神经网络缺陷识别

设计的 CNN 网络^[21-22]如图 10,由两个卷积层、两个池化层和两个全连接层组成,其中两个卷积核的大小均为 3×1 ,数量分别为 64 和 32;池化方法选择最大池化,池化核尺寸均为 2×1 ;两个全连接层的输出分别为 500 和缺陷类型数量。选取 SGDM 优化算法,学习率初始值设为 0.001,采用 Softmax 激活函数实现对缺陷的识别, classoutput 激活函数进行分类输出。

针对标准焊接和夹杂、未熔合热熔缺陷构建第一类缺陷识别模型,用于不同种缺陷的定性分析;针对标准焊接和夹杂金属、粗沙、树枝缺陷构建第二类缺陷识别模型,用于夹杂类缺陷的定量识别。将数据集中 80% 划分为训练集,20% 划分为预测集,如表 1。

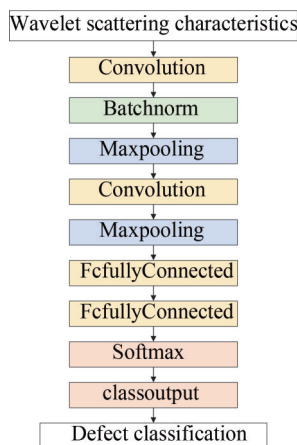


图 10 CNN 网络架构
Fig.10 CNN Network architecture

表 1 数据集属性表
Table1 Dataset property table

Sample types	First model defect type/Number of data sets	Second model defect type/Number of data sets
Standard welding	BZHJ/3 000	BZHJ/3 000
Incomplete fusion	WRH/3 000	/
Inclusion metal	JZ/1 000	JS/3 000
Inclusion of coarse sand	JZ/1 000	CS/3 000
Inclusion branches	JZ/1 000	SZ/3 000

第一类识别模型每个迭代的准确度和损失如图 11,使用该训练模型测试结果的混淆矩阵如图 12。该识别模型在经过 2 602 次迭代后的准确率为 99.5%,达到训练要求,在预测集中对夹杂类缺陷的预测正确率为 99.3%,其中有 8 个错判为标准焊接,13 个错判为未熔合缺陷。对标准焊接的预测正确率为 99.9%,其中有 1 个错判为夹杂缺陷,2 个错判为未熔合缺陷。对未熔合缺陷的预测正确率为 98.0%,其中有 42 个错判为夹杂缺陷,18 个错判为标准焊接。

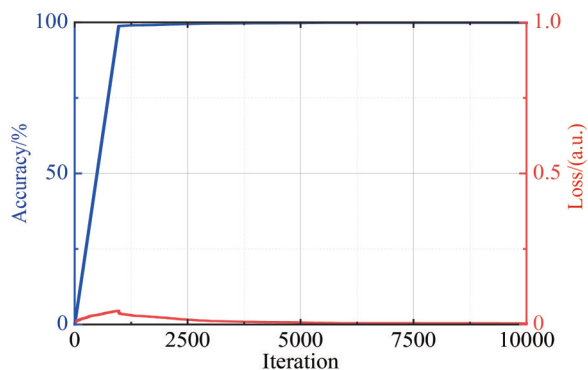


图 11 第一类识别模型每个迭代的准确度和损失
Fig.11 Accuracy and loss of each iteration of the first training model

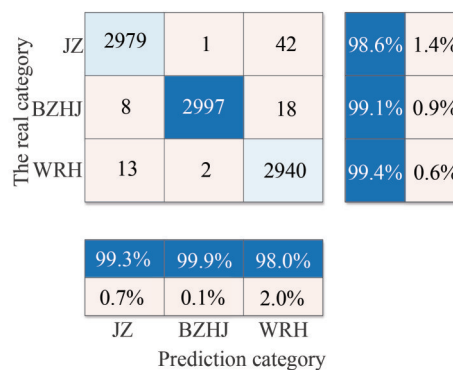


图 12 使用第一类识别模型测试结果的混淆矩阵
Fig.12 Confusion matrix of test results using the first kind of training model

第二类训练模型每个迭代的准确度和损失如图 13,使用该训练模型测试结果的混淆矩阵如图 14。该训练模型在经过 1 710 次迭代后的准确率为 99.5%,达到训练要求,在预测集中对夹杂金属的预测正确率为 99.5%,其中有 2 个错判为标准焊接,7 个错判为夹杂粗沙,6 个错判为夹杂树枝。对标准焊接的预测正确率为 99.7%,其中有 1 个错判为夹杂金属,1 个错判为夹杂粗沙,6 个错判为夹杂树枝。对夹杂粗沙的预测正确率为 97.9%,其中有 16 个错判为夹杂金属,10 个错判为标准焊接,37 个错判为夹杂树枝。对夹杂树枝的预测正确率为 98.1%,其中有 12 个错判为夹杂金属,14 个错判为标准焊接,31 个错判为夹杂粗沙。

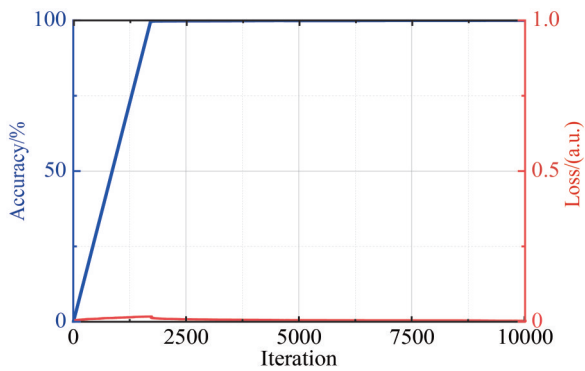


图 13 第二类训练模型每个迭代的准确度和损失
Fig.13 Accuracy and loss of each iteration of the second training model

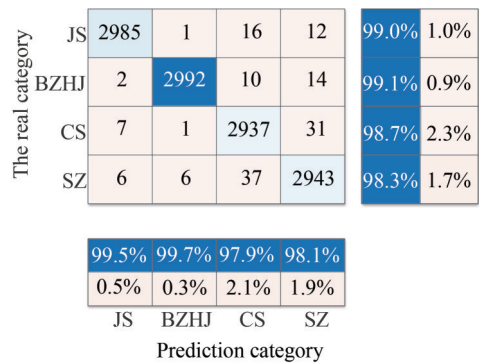


图 14 使用第二类训练模型测试结果的混淆矩阵
Fig.14 Confusion matrix of test results using the second kind of training model

第一类缺陷识别模型的识别率均可达到 98% 以上,由于未熔合接头样件是焊接面积不同使其未贴合制作而成,在焊接过程中的压力作用下使得预置缺陷与实际缺陷面积相差过大,因此只用于定性分析。由高精度 CT 测得夹杂金属 1、夹杂金属 2、夹杂粗沙、夹杂树枝检测面对应的面积 S 和系统的检测步距 R ,得到理论检测数据点个数 N ,即 $N = S/R^2$,并将夹杂类缺陷样件的 THz 波形数据分别导入训练好的两种缺陷识别模型中进行识别分类,其缺陷识别数量与实际数量对比图及误差曲线分别如图 15、图 16。第二类缺陷识别模型对缺陷有较好的识别水平,其识别误差均在 7.42% 以下,对粗沙的识别的误差可达 2.57%。此外,还讨论了第一类缺陷识别模型对夹杂类缺陷的效果,其误差均在 8.02% 以下。

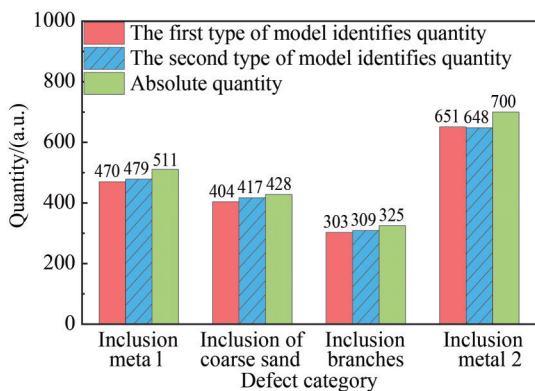


图 15 两种训练模型缺陷识别数量与实际数量对比
Fig.15 The comparison chart between the number of defect recognition and the actual number of two training models

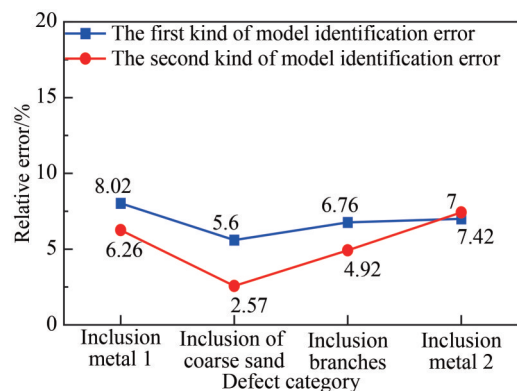


图 16 两种训练模型缺陷识别数量与实际数量误差曲线
Fig.16 Curve diagram of error between the number of defect recognition and the actual number of two training models

4 结论

针对聚乙烯管道实际热熔焊接中的接头缺陷,制作了聚乙烯标准热熔焊接样件和过焊、冷焊、夹杂及未熔合缺陷热熔接头样件,采用反射式脉冲太赫兹时域光谱技术对其进行检测,分析了不同缺陷类型的太赫

兹波形信号特征及峰度成像图中缺陷的大小和位置。针对不同缺陷种类分别构建小波散射网络-卷积神经网络缺陷识别模型实现对不同接头缺陷的定性定量识别,对标准焊接、未熔合缺陷以及夹杂类缺陷识别率均可达到98%以上,对夹杂类缺陷识别相对误差均在7.42%以下。本文研究为太赫兹无损检测技术在聚乙烯管道热熔接头检测中的应用奠定基础。

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Terahertz Identification of Hot Melting Joint Defects in Polyethylene Pipe Based on Wavelet Scattering Network

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Abstract: Polyethylene pipelines have become the first choice in the field of gas and oil pipelines due to their advantages in corrosion resistance, plasticity and cost performance. Because of their flammable and explosive characteristics, natural gas and oil are prone to safety hazards, so the quality should be strictly controlled in production and use. PE pipes are usually welded on site during laying. Human factors, long-term weathering and corrosion effects in the welding process may lead to defects in the welded joints of pipes. Therefore, the quality inspection of welded joints of pipes is particularly important. At present, the detection methods of hot-melt joints mainly include ultrasonic testing, infrared thermal imaging detection, ray detection, etc. These detection methods have certain limitations in the actual polyethylene pipeline detection.

As a non-destructive, non-ionizing, non-contact new detection technology, Terahertz non-destructive testing technology has a strong penetration of non-polar, non-metallic materials. The non-destructive testing technology based on THz imaging technology can obtain the frequency domain, time domain and spatial information of the tested sample, and can clearly image the defects of the material. With high defect detection and positioning ability, it is gradually gaining prominence in the field of non-destructive testing, which can be used as an effective supplement to traditional testing technology.

In order to solve the problems of cold welding, over-welding, non-fusion and inclusion defect detection of PE pipe hot-melt joints, reflective pulsed terahertz time-domain spectroscopy with a frequency range of 0.25~2.5 THz is used to detect PE hot-melt joints. The hot-melt welding between PE100 sheets is used to simulate the actual hot-melt welding of polyethylene pipes. Standard hot-melt welding and cold welding, over welding, incomplete fusion and inclusion hot-melt defect joint samples are made. Through point-by-point scanning of terahertz system, the wave pattern and kurtosis imaging at the joint are obtained. In the wave pattern, there is little difference between the cold welding and over welding defect samples and standard welding samples, with obvious differences between inclusion defects and incomplete fusion defects and standard welding samples. The unfused and mixed hot melt defect samples and standard welding samples have obvious difference in waveform, the surface reflection echo of unfused defect is about 50% of the standard welding, the surface echo of mixed defect is between 20% and 40% of the standard welding. In kurtosis imaging, the weld width of cold welding and over welding defects is larger than that of

standard hot fusion welding, and there are defects in the weld. Incomplete fusion defects and inclusion defects can clearly see the rough outline of the defect part. The first kind of wavelet scattering network-convolution neural network defect recognition model is constructed for standard welding, inclusion and incomplete fusion defects. The defect recognition rate can reach more than 98%. The second kind of defect recognition model is constructed for quantitative identification of standard welding and metal inclusion, coarse sand and branch defects. The relative error of defect recognition is less than 7.42%. This study lays a foundation for the application of terahertz non-destructive testing technology in the detection of polyethylene pipe hot-melt joints.

Key words: Terahertz; Non-destructive testing; Polyethylene hot melt joint; Wavelet scattering network; Defect identification

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