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题目 基于深度学习的雷达信号处理

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指 导 教 师 山

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博 士 学 位 论 文

(学位研究生)

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2016 年 9 月

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Title: Radar Signal Process Based on Deep Learning

By
Zhishan Zhang

Under the Supervision of Professor
Shan

A Dissertation Submitted to
Northwestern Polytechnical University

In partial fulfillment of the requirement
For the degree of
Doctor of Math

Xi'an P. R. China
September 2016

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摘要

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关键字： 中文, 摘要

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Abstract

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Keywords： English, Abstract

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1.1 引言

而是

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短发

1.3 辐射源类别识别

辐射源的快速、准确和鲁棒的自动目标识别在现代军事中的作用十分重要，自动目标识别算法需要可以准确区分出已知目标和未知目标，同时可以正确的对于已知目标进行分类。我们需要在未收集大量数据的前提下，可以迅速的识别出新的目标。与传统的利用已知类别的样本进行训练测试的机器学习算法不同，我们这个问题是在 Open Set 的情况下，将需要考虑将输入识别为未知的情况。本文利用深度卷积神经网络与支持向量机进行结合，以雷达信号的模糊函数作为训练样本，构建了一个可以对未知分类进行识别的分类器。我们利用实际数据进行验证，证明我们的分类器具有很强的准确性。随着科学技术的进步，现代战场形势瞬息万变，信息对抗在现代军事中的作用越来越重要。纵观整个 20 世纪所爆发的两次世界大战和数次局部战争、21 世纪初的美阿、美伊之战以及最近闹得沸沸扬扬的韩国的萨德事件，无一不昭示着现代战争已成为电子战的“天下”，电子战技术也在历次实战演练中逐渐成熟。电子战也称电子对抗，包括电子侦察、电子攻击和电子防护三个方面。电子侦察主要指从敌方雷达及其武器系统获取有用信息, 通过雷达辐射源个体识别，可以对战场环境中敌我双方雷达辐射源的分布情况实施侦察，提供更加全面的、精确的电磁斗争与武器的态势，进行有效的战场指挥与决策，雷达辐射源个体识别已成为当前电子战特别是电子侦察领域的研究热点和难点。然而由于辐射源的特征未知、信号波形日趋复杂、战时电磁环境恶劣，给辐射源的精确识别带来了越来越严峻的挑战。

在雷达辐射源信号特征挖掘方面, 已有很多学者作了大量研究工作, 在上世纪 70 年代国外相关研究人员就开始了该部分的研究，该部分研究可以分为两个阶段: 第一阶段

为辐射源基本参数特征研究。对于原始信号特征直接求取其载波频率、脉冲宽度、脉冲幅度、到达角度和到达时间等信息，利用其中一个或多个作为特征向量。这种情况主要是应用于电磁环境相对单一、辐射源类别较少、信号形式单一、雷达参数固定的早期。

第二阶段自 20 世纪 90 年代以来，西方的军事强国开始研究雷达辐射信号的脉内特征，相继提出了了多种分析雷达信号脉内特征的方法。有代表性的工作有: 时域波形分析法、谱相关法、基于专家知识信号处理法、时频综合法、小波分析法、信息理论准则与聚类技术综合法、脉内瞬时频率特征与累积法、信号的分型特征等。

国内对雷达辐射源个体识别技术的研究始于上世纪 80 年代初，虽然起步较晚，但受到了军方的高度重视，在“九五”、“十五”和“十一五”国防预研中给予了大力资助。在脉内特征挖掘方面，毕大平提出易于工程实现的脉内瞬时频率提取技术；张葛祥提出了雷达辐射源信号的小波包特征、相像系数特征、熵特征、粗集理论、信息维数和分形盒维数；朱明提出了基于原子分解的特征、基于 Chirplet 原子的特征、时频原子特征；普运伟提出了瞬时频率派生特征、模糊函数主脊切面特征；陈稻伟提出了符号化脉内特征、围线积分双谱特征等；余志斌提出的局域波分解、小波脊频级联特征。

另一方面，雷达辐射源识别是一个典型的分类问题，其主要思路为在得到辐射源信号的特征表示之后，借助有效的分类算法来实现特征空间到决策空间的转换，从而确定信号的所属类别。大量的分类算法被成功运用于雷达辐射源识别中，如模板匹配、神经网络、支持向量机等。一般被应用于该领域的有三种分类方法，一种是判别型分类器，其需要在学习过程中最优化某种目标函数；另一种为生成模型分类器，其主要是基于先验概率和类别条件概率密度进行估计，如线性判别分类器、K 最近邻等；第三种是决策树分类算法，通过人类专家的先验知识进行分类，如 ID3、C4.5 算法。

1.4 论文研究内容及结构

2　深度卷积神经网络

深度学习是指具有超过一个隐藏层的神经网络结构，其起始于在 2006 年发表在顶尖学术刊物《Science》上的一篇文章，可以算作机器学习的一个分支，其于传统的机器学习方法的主要区别为，其通过隐藏层的人工神经网络结构学习得到数据更本质的特征以及通过逐层初始化来克服传统算法在训练上的难度。自从被提出来至今，其在工业界以及学术界掀起了巨大的浪潮，被应用于语音识别、图像识别、自然语音处理和推荐系统等各种方面。

2.1　基本分类

传统上可以把深度学习分为卷积神经网络（CNN）、递归神经网络（RNN）、长短时记忆网络（Long short-term memory, LSTM）, 深度信念网络（DBN）等，其中卷积神经网络是最流行的一种深度学习模型。本课题主要利用的是卷积神经网络，通过使用卷积层极大地减少了中间层的参数数目，使学习效率更高并较少过拟合，同时卷积操作独有的局部感受野（local receptive fields）、共享权重（shared weights）和池化（pooling）三种特性也是处理序列元素分类识别的很重要的一点，权重共享策略减少了需要训练的参数，相同的权重可以让滤波器不受信号位置的影响来检测信号的特性，使得训练出来的模型泛化能力更强；池化运算可以降低网络的空间分辨率，从而消除信号的微小偏移和扭曲。

递归神经网络是一种包含循环的，允许信息持久化的神经网络模型。传统的前馈神经网络中，单独的输入完全确定了余下层的神经元的激活值。而对于 RNN，隐藏层和输出层的神经元的激活值不仅由当前的网络输入决定，而且包含了前面的输入的影响。长短时记忆网络是一种 RNN 特殊的类型，主要用于解决 RNN 的前期模型难以训练的问题。其通过刻意设计的单元结构，在 RNN 的基础上添加了元胞状态（cell state）用来保存长期的状态，然后通过门函数来控制此长期状态。

深度信念网络是一个概率生成模型，是由多个限制玻尔兹曼机（Restricted Boltzmann Machines）组成，这些网络被“限制”为一个可见层和一个隐藏层，层间存在连接，但是层内的单元间不存在连接。隐藏单元被训练来捕捉在可见层表现出来的高阶数据的相关性。

从上述的介绍可以看出，CNN 是最适合处理本课题这种静态类型的数据，循环或

者说是不同时刻的输入对于地海杂波类型的识别并没有提高，故 RNN 和 LSTM 显然不适合本问题。另一方面，DBN 的生成模型并不关心不同类别之间的最优分类面的位置，故其用于分类问题时，分类精度没有判别模型高。且其学习的是数据的联合分布，相比其他算法具有更高的复杂性。

2.2 传统神经网络

2.3 深度卷积神经网络

神经网络是有多个图 23 中的人工神经元组成，神经元具有多个输入 $x_1, x_2, \ldots$ ，这些输入可以取 0 和 1 中的任意值。神经元对于每一个输入有权重 $w_1, w_2, \ldots$ 和一个总的偏置 b_0 ，其输出为一个 $\sigma(w \cdot x + b)$ ，这里的 σ 为该神经元的激活函数，定义为：$\sigma(z) \equiv \frac{1}{1+e^{-z}}$ ，此处的激活函数称作 S 型激活函数，常使用的还有 $ReLU$ 等激活函数。

图 27 神经元其基本架构如图 24 所示，最左边的为输入层，其中的神经元为输入神经元。最右边的输出层包含有输出神经元，可以有一个也可以由多个。中间层为隐藏层，这部分为需要进行主要设计，也是各种神经网络模型的主要区别之处。为了增强其泛化能力，一般情况下有扩增路径（将多个分支包含在架构中）、金字塔形状（在整个架构中应该有一次整体的平滑的下采样，而且该下采样应该与信道数量的增长结合起来）、规范层输入（使层输入标准化，使所有输入样本更加平等）等各种设计法则，此部分需要根据实际问题以及测试结果不断调整。

2.3.1 卷积

深度卷积神经网络在特征提取过程中一个主要操作为卷积，在前向计算过程中，对于输入的一定区域的数据和滤波器（或者说权重）点乘后得到新的特征向量，然后滑过一个个滤波器，组成新的输出数据。每个滤波器只关心数据的部分特征，当出现它学习到的特征的时候，就会呈现激活态。$s(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a)$

2.3.2 局部感受野

：对于传统的神经网络，每个输入元素会连接到每个隐藏神经元。相反，我们只是把输入的频谱数据进行小的、局部区域的连接，也即第一个隐藏层中的每个神经元会连接到一个输入神经元的一个区域。这个输入向量的区域被称为隐藏神经元的局部感受野。它是输入向量上的一个小窗口，对于每个连接学习一个权重而隐藏神经元同时

也学习一个总的偏置。通过在整个输入频谱数据上交叉移动局部感受野，可以构建起第一个隐藏层。

2.3.3 共享权重和偏置

上面已经说过对于每个隐藏神经元具有一个偏置和连接到它的局部感受野的权重，同时对于该层的所有的隐藏神经元中每一个使用相同的权重和偏置。也即，对第个隐藏神经元，输出为：$\sigma(b+\sum_{m=1}^{M} w_m a_{j+m})$ 这里是神经元的激活函数，是偏置的共享值，是一个共享权重的向量，表示位置的输入激活值。这意味着第一个隐藏层的所有神经元检测完全相同的特征，只是在输入频谱数据的不同位置，因此卷积网络可以很好地适应频谱数据的布拉格峰偏移情况。

2.3.4 池化

我们在通过卷积获得了特征之后，下一步我们希望利用这些特征去做分类。理论上讲，人们可以用所有提取得到的特征去训练分类器，例如分类器（多分类的逻辑回归分类器），但这样做面临着计算量的挑战，除此以外过多的特征向量，也容易导致过拟合。

由于我们的杂波频谱数据具有一种“静态性”属性，在一个数据区域有用的特征极有可能在另一个区域同样适用。因此，为了描述数据量较多的数据，一个很自然的想法就是对不同位置的特征进行聚合统计，例如，可以计算频谱数据上一段频率范围内的某个特征的最大值 (或平均值)。这些经过采样的统计特征相比使用所有提取得到的特征不仅具有低得多的维度，同时还不容易过拟合，在一定程度上会改善结果。这种聚合的操作称为池化，常用的池化方法有平均池化和最大池化。本课题选择频谱向量中的连续范围作为池化区域（池化长度为 2），并且只是池化相同的隐藏单元产生的特征。由于这些池化单元具有平移不变性，所以即使频谱数据的布拉格峰经历了一个小的平移之后，依然会产生相同的池化的特征。

深度卷积神经结构具有过拟合的自然趋势，虽然可以通过权重共享来减少参数的数量。但是由于大多数情况下，估计集的数量比训练集大一个数量级，使得神经网络模型的泛化能力不足。在每个训练迭代中，每个隐藏单元以预定概率（我们将其设为）被随机删除，删除后学习过程继续。这些被称作的随机扰动有效地防止了神经网络学习过程的依赖关系，并在隐藏的单元之间创建了复杂的关系。这样增加了网络模型的复杂度，从而提高深度神经网络模型的泛化能力。

2.3.5 网络的训练与学习

如果用符号 x 表示一个训练输入，用 $y = y(x)$ 表示对应的期望输出。学习算法的主要目的是，找到一个权重和偏置，使得网络的输出 $y(x)$ 可以拟合所有的训练输入 x 。为此可以定义一个损失函数（又称作代价函数）：$C(w,b) \equiv \frac{1}{2n}\sum_x ||y(x) - a||^2$ 这里 w 表示所有的网络中权重的集合，b 是所有的偏置，n 是训练输入数据的个数，a 是表示当输入为 x 时输出的向量，求和总是在总的训练输入 x 上进行的。上述损失函数为均方误差，其是可以根据不同的问题进行不同的设置的。从定义可以看出，$C(w,b)$ 越小说明分类越准确，那么训练神经网络的目的就是找到最小化二次代价函数 $C(w,b)$ 的权重和偏置。将上述问题一般化也就是，最小化任意的具有 m 个变量的多元实值函数 $C(v)$，$v = v_1, v_2, \ldots, v_m$。对于这种具有大量变量的函数的解析解是极其复杂的，其比较合理的思路为利用数值计算的方法求取其极值点。每次对于 C 中的自变量添加一个微小的变化 Δv ，根据此变化反映出来的 C 的变换 ΔC 更新下次的微小变化，从而使得 C 可以持续减小。对 C 中自变量的变化 $\Delta v = (\Delta v_1, \ldots, \Delta v_m)^T$ ，ΔC 将会变为 $\Delta C \approx \bigtriangledown C \cdot \Delta v$ ，这里的梯度 $\bigtriangledown C$ 定义如下：

$\bigtriangledown C \equiv (\frac{\partial C}{\partial v_1}, \ldots, \frac{\partial C}{\partial v_m})^T$ 其把 v 的变化关联为 C 的变化，假设我们选取 $\Delta v = -\eta \bigtriangledown C$ 这里的 η 是一个很小的正数（称为学习速率），这时候有 $\Delta C \approx -\eta \bigtriangledown C \cdot \bigtriangledown C = -\eta || \bigtriangledown C||^2 \leq 0$ 也即如果利用更新规则 $v \rightarrow v' = v - \eta \bigtriangledown C, C$ 会持续减小，此更新规则即为梯度下降算法，这就是最基本的学习算法。可以根据选择不同的代价函数 C 或者通过计算来完成学习速率的选择等各种技术对学习算法进行优化。

2.4 深度卷积神经网络在雷达信号处理中的应用

3 基于深度学习的天波超视距雷达地海杂波识别

3.1 Introduction

Over-the-horizon radar (OTHR), operates in the high frequency band, is able to detect and localize moving targets in areas beyond the horizon via ionospheric reflection, and therefore plays an important role in persistent surveillance [1, 2]. However, the propagation of electromagnetic signal through ionosphere leads to a mandatory procedure, coordinate registration (CR), for target localization, since the positions of targets in ground coordinate system (i.e., latitude and longitude) are required but OTHR receives measurements in slant coordinate system (i.e., slant azimuth and slant range) [3]. To perform CR, two sub-steps have to be invoked, (1) selecting the right ionosphere propagation mode for each measurement or target's state estimate, (2) transforming the measurement or target's state estimate from slant coordinate system to ground coordinate system.

In general, a sub-system consists of several ionosondes is deployed and operated with OTHR to provide the information required by CR. The information includes the possible ionosphere propagation modes and the corresponding parameters for each propagation mode, such as the height of each layer of the ionosphere [4]. OTHR takes such information from ionosondes as the input of it and achieves CR. There are two factors that may deteriorate the localization performance of OTHR using ionosondes. The first one is that the deployment of ionosondes is restricted to available areas. For example, ionosondes can not be deployed in the sea or hostile areas. The ionosphere's parameters of unavailable areas are often obtained by interpolation with those of available areas based on statistical ionospheric models, making the information input into CR inaccurate. The second one is that the independent operation of ionosondes from OTHR results in consistency on the number of propagation modes and inaccuracy on the parameters for each propagation mode. More specifically, the propagation modes recognized by ionosondes may not the same as the propagation modes that the measurements received by the OTHR originate from. Therefore, to reduce the chances of incorrect identification of propagation mode for each measurement or state estimate, and the effect caused by the error of parameters provided by ionosondes so that improve the accuracy of CR, alternative methodologies have to be sought.

One way available to improve CR is using beacons [5]. OTHR receives the signals transmitted by beacons and outputs the measurements on their locations in slant coordinate system. By comparing the measurements with known locations of beacons in ground coordinate system provided by GPS, correction on the CR process can be carry out in real-time. However, the utilization of beacons is restricted to available areas as well. Additionally, maintenance on beacons is needed.

In fact, another source, sea/land transitions, can be regarded as a kind of passive beacons since the same principle is applicable if the signals of sea and land are identifiable. The idea of using coastline for CR is first appeared in [4, 6], where no detailed results were reported. Barnum *e*t. al. [7] proposed a CR method based on sea/land clutter identification, which mainly relies on constructing the clutter model. However, due to the complexity of ionospheric situation, the characteristics of the sea/land clutter is not stable, for example, one of the main features of sea clutter, Brag peak, may shift or even lost one peak.

In [8, 9, 10, 11], In this paper, we propose an approach to the problem of real time coordinate registration for Over the Horizon Sky Wave signals. The approach is based on the a priori knowledge of the displacement of the sea-land transitions within the radar coverage area, namely, takes advantage of the geo-morphological structure of the surveillance area, employing it to build a binary mask to be used as a geographic reference for the received radar echo. The georeferencing algorithm, based on the maximization of the cross-correlation between the received radar echo and the binary clutter signatures, is outlined in order to point out the minimum requirements in terms of received signal-to-noise ratio and differential sea-land backscattering coefficient.

In [9], We recently proposed a correlation method for the real time Coordinate Registration (CR) of the received echo by Over The Horizon Sky Wave Radar (OTHRsw) based on a priori knowledge of the positions of the Sea-Land transitions within the radar coverage area. In this paper we present a software simulation tool developed to analyze the performance of the proposed CR method in different OTHR scenarios. The software tool simulates the monostatic OTH radar propagation using simplified ionospheric models and simplified models of surface clutter radar interactions. Simulation results assuming different surface clutter scenarios are presented and discussed.

In [10], We recently proposed a correlation method for the real time Coordinate Registration (CR) of the received echo by Over The Horizon Sky Wave Radar (OTHR-SW) based on a priori knowledge of the positions of the sea-land transitions within the radar coverage area. In this paper we present a simulator that can be used for performance analysis of the proposed CR method in realistic OTHR scenarios. Some simulation result are presented and discussed assuming a single sea-land transition scenario and a geographically invariant vertical electron density profile.

In [11], Cuccoli *e*t. al. studied the problem of range coordinate registration leveraging the geomorphological structure of the surveillance area. The geographical information including coastlines is represented by sea/land binary mask, which is further converted to a reference signal depending on the equivalent ionospheric reflection height. The right equivalent ionospheric reflection height is determined by maximizing the cross-correlation between the received radar echo and the surface mask signatures. However, they assume the OTHR transmits single pulse signals and numerical simulation results are provided.

In [12], Target detection in Over-The-Horizon (OTH) radars is accomplished by tracking returns in slant range, Doppler and azimuth. Coordinate registration (CR) is the process of localizing the target by converting the slant coordinates to ground coordinates for all the frequencies used in transmission. The CR method uses a 3D ray-tracing algorithm which provides the ground range distance reached with a specific transmission frequency and elevation angle. The ray-tracing approach here adopted uses a 3D electron density model variable with height, latitude and longitude. The ray-tracing output is generally affected by errors due to numerical approximations of the 3D ionosphere model and discretization step used to integrate the differential equations of ray-tracing algorithm. Therefore the raw CR diagram suffers from an error which introduces as a consequence a degradation of target localization accuracy. Accordingly, we propose a coordinate registration technique for OTH sky-wave radars based on 3D ray-tracing that uses the sea-land transitions to mitigate the CR errors. The approach is based on the a priori knowledge of actual group delays relative to the sea-land transition within the area illuminated by the radar antenna beam. The method takes advantage of the geomorphological structure of the surveillance area. The errors introduced by the 3D ray-tracing software are then evaluated by using the actual group delay sat sea-land transitions.Afterwards, the estimated errors are used to correct the coarse CR diagram that was obtained straightforward from the ray-tracing output. Finally, the proposed correction method has been verified under the simplified assumption of a horizontally stratified ionosphere.

In [13], A skywave over-the-horizon radar (OTHR) can detect and track aircraft or surface targets at ranges of 1000 to 3000 km by reflecting high frequency (HF) signals from the ionosphere. Coordinate registration (CR) is the process of registering OTHR tracks from radar to geographic coordinates. CR is often performed by ray-tracing through a real-time ionospheric model (RTIM). Opportunistic scatterers that produce identifiable radar returns from known reference points (KRPs) may also be exploited for CR. To complement traditional passive KRP sources, this paper investigates the use of uncooperative emitters of opportunity as active KRP sources to enhance OTHR track geo-registration accuracy. A method that utilizes a HF radio broadcast signal as an active KRP source for CR is presented and analyzed using experimental data from the Australian Jindalee OTHR network (JORN).

In [14], Skywave radar exploit the ionospheric medium to illuminate and track targets at long ranges over vast areas. To achieve optimal performance in the dynamic clutter and noise environment cognitive radar techniques are used to advise waveform parameter and coordinate registration for localisation of targets. Here we introduce an experimental high spatial resolution support-radar that remotely senses surface backscatter clutter. A robust algorithm is described for analysis of the Doppler spectra to determine land or sea backscatter origin. The sensed land-sea interfaces can thus be used for direct registration of nearby targets or assimilation into an ionospheric map.

In [15], High fidelity electromagnetic modeling of the wave propagation field is essential to accurately assess the impact of wind-turbine modulated ground clutter on high frequency (HF) Over-The-Horizon (OTH) radar performance. To support the modeling effort, field measurements were conducted in 2014 near the AN/TPS-71 HF Relocatable Over-the-Horizon Radar (ROTHR) in Virginia to investigate wave propagation near the ground. Extensive propagation data were collected by transmitting from a helicopter-borne HF transmitter to a number of monopole antennas on the ground near the ROTHR receive site at three HF frequencies (7.5 MHz, 14.5 MHz, and 23.5 MHz) and various elevation angles from five to zero degrees (grazing incidence) as measured from the receive antenna. The measurement ranges varied from 5 to 40 km and the helicopter altitudes varied from ground level up to 6000 feet. The measurement results are well correlated with model-based predictions for a smooth-homogeneous-earth surface provided that the ¡°effective¡± dielectric constant and conductivity of the terrain are reduced from their expected values as estimated from in situ soil samples and the National Land Cover Database.

In [16], Skywave over-the-horizon radar exploits ionospheric propagation to detect and track targets at long range over vast areas. To achieve optimal performance in the dynamic propagation, clutter and noise environment cognitive radar techniques are used to inform waveform parameter selection and improve coordinate registration for localization of targets. In this paper we investigate the use of Earth surface and infrastructure backscatter to aid in coordinate registration. A transponder was placed in the vicinity of a window turbine farm and a mountain range producing strong backscatter. Terrain echoes are shown to provide similar azimuth-range-Doppler information to the transponder echo with similar temporal coverage. Wind turbine echoes are shown to provide azimuth-range information albeit with less temporal coverage than the transponder and terrain echoes.

Therefore, some authors present a method using passive islands as benchmark to find the PD transform coefficient[11]. We can search for the location of the islands in measurement coordinates by identifying sea/land according to spectrum data and then correspond them with islands in the radar coordinates. Thus, we can get PD transforming coefficient according to the deviation of the same location benchmark. Therefore, the most basic and most critical part of this method is identifying sea/land clutter.

All the above mentioned publications,focused on To the best of our knowledge, the only work that has considered sea/land clutter recognition was the work of Jin *e*t. al. [17] and Jin et al. [17] proposed a recognition algorithm based on support vector machine (SVM). They train SVM by using three types of features of sea/land clutter, and verified it with simulation data. In the actual situation, characteristics of the sea/land clutter depend on the ionospheric environment at that time, the sweeping angle of the radar, the weather environment and so on. There are numerous uncertainties in the modeling of sea/land clutters. When the parameters required for modeling change, the accuracy of the algorithm will drop sharply. In 2013, Li et al. [18] use a neural network method to an aircraft detection problem, which is similar to our problem.

In this paper, we adapt deep learning methodology, specifically deep convolution neural network to solve the sea/land clutter recognition for OTHR. By analyzing the characteristics of the sea/land clutter received by OTHR, we find that ... which are qualified for the advantages of classifiers based on deep learning methodology.

One is to build the ionospheric statistics model based on prior knowledge and the other one is to gather information by some detection equipment. Both approaches meet some limitation, the former cannot update timely and sometimes get a critical error(i.e. the weather mutation takes place), the latter needs lots of devices and it is not easy to place them in the sea.

We implement our experiments using spectrum data in different ionospheric conditions, radar working conditions, geography, and time. Different times and geographies will correspond to different ionospheric conditions, and different ionospheric conditions will seriously affect the status of the spectrum. For different radar working conditions, due to the transmission and acceptance of the wave frequency changes, the spectral density and amplitude will change. By watching a large number of different conditions of the spectrum data, we can get a more comprehensive understanding of sea/land clutter spectrum.

3.1.1 Sea/Land Classification Analytic

The coordinate registration problem of sky-wave over-the-horizon radar targets affects its tracking accuracy to a large extent, especially for the remote area where the ionospheric parameters cannot be obtained accurately and timely. There are two main advantages to the recognition of sea/land clutter. The first is that we can use the acquired clutter topographic map to match the actual map, and then calculate the offset, according to the matching result, which can be used to improve the accuracy of target tracking, and on the other hand, we can correct the spectrum itself by using the offset on the spectrum obtained by the recognition result to improve the probability and accuracy of the target detection.

Sea/Land classification for spectrum data has two unique challenges. The first is clutter model complexity: it is difficult to model the clutters, cause it changes all the time. There are different types of distribution to describe the radar clutters, Rayleigh distribution, Weibull distribution, K distribution and so on, but none of them can lead to a good result all the time. Second, features of classical sea and land are not easy to distill. We may know it easily artificially, but it is nearly impossible to describe these features accurately. In this paper, we present and evaluate a convolution neural network method that overcomes these challenges. Our algorithm applies CNN to sea/land clutter identification. We avoid the modeling of sea/land clutter, which fundamentally avoids the difficulties faced by traditional methods.

We evaluate the quality of two algorithms, one classification using SVM and one using CNN, against the baseline based on the single threshold method, on several spectrum datasets. Overall, we find that:

- We can get the best results in our method based on convolution neural network, which can lead a big differences in pairing to the map.
- Our method has great robustness. The changes in parameters makes a little affect on results.

We note that the overall purpose of our work is to assess the feasibility of a convolution neural network-based algorithm for sea/land classification. The improvement of this algorithm over the SVM shows it is usable for this problem. However, alternate network configurations tuned to specific spectrum dataset can be expected to result in higher quality.

3.1.2 Our Methodology

Convolution neural network(CNN) is an important algorithm in deep learning and has great superiority in classification and other fields. This method is frequently used to deal with picture recognition, speech recognition and other issues. It does convolution operation for the original data and then extracts the feature of convolution data generated from the last step, which enriches the features used in the recognition greatly. At the same time, it can reduce the computational complexity due to merging some of the adjacent features. By applying CNN to sea/land clutter identification, we avoid the modeling of sea/land clutter, which fundamentally avoids the difficulties faced by traditional methods. We build a three-layer convolution neural network combining our specific problems. On this basis, we use the same sample to train and test SVM method and our algorithm separately. The experiments results demonstrate the stability and accuracy of our algorithm in the actual situation. Our sea/land clutter identification problem is based primarily on the characteristics of the spectral data to identify. The artificial identification depends mainly on the existence of a Bragg peak in sea clutter or only one peak near zero frequency in land clutter. However, there are still some remaining features, that cannot be found very clearly artificially, such as the overall amplitude and so on. Besides, there are still some useless features in some spectrum data, for example, a target appears, which can be easily excluded through the volume and feature extraction and weight sharing. Thus, a method based on CNN fits our problem strongly.

In summary, our novelty here is twofold:

- We propose a method for sea/land classification from spectrum data using a novel set of features in a convolution neural network, overcoming the challenge of traditional algorithms.
- We show that an average of spectrum data in the same area from different time can improve the classification precision greatly.

3.2 Sea/Land Classification Algorithm

In 1982, Neocognitron presented by Kunihiko Fukushima[19] introduced the concept of the first deep learning model, CNN for the first time. Later, many scholars have made a significant contribution to the development of CNN in practice and theoretical analysis. In 1989, LeCun and others presented the gradient-based learning method[20] and BP algorithm[21] into CNN. In 2003, Behnke wrote a book summarizing CNN[22]. In the same year, Simard and others have simplified CNN[23]. In 2011, Ciren et al. improved CNN further and implemented its GPU version[24], after which they used the CNN framework to experiment with multiple image databases and achieved the best results ever.

In this section, we first introduce the input and output variables of our algorithms, and then describe our algorithm design and evaluation method.

3.2.1 Input Features and Classification Result

In the traditional classification problem, there may be a variety of different characteristics of the data combination to be classified. Here, what we used to do the sea/land clutter identification is clutter spectrum data. But in order to formulate the problem more relevant, we have dealt with the characteristics of the input training.

We do not select the complete clutter spectrum data of the specific distance azimuth unit as the input feature, but rather that the differences between our land and sea clutter are mainly concentrated.In fact, the frequencies range that kick in is only a small part around zero(the characteristic is also verified in the feature visualization part). We cut the original spectrum data and only select the smaller part of the data. By reducing a lot of useless data, we reduce the amount of calculation at the same time to a certain extent preventing the emergence of over-fitting.

On the other hand, we obtain the data in the frequency domain by the fast Fourier transform of the original time domain data. Although it seems that the frequency domain is similar to the case where both the training and test are in the time domain. However, in practice, since the position of the time domain corresponding to the frequency domain during the training process is different, it is more accurate to use the data in the frequency domain when the convolution operation is performed. Because the feature is more concentrated and available for the convolution learning.

Classification Probability

As our problem is a binary classification problem, what we get is a probability that the spectrum data are sea/land clutters. In general condition, we may use 0.5 as a baseline to divide them. However, in our question, there are two different aspects:

- The variability of the sea is much greater than the land. It is easy to identify a sea as land mistakenly.
- The sea/land should be continuous, because the resolution unit is small enough that it is impossible to have such a small island surrounded by the sea.

Therefore, we cannot output the results directly. We need to find a suitable threshold to divide the sea/land clutter, which will be discussed in later section. Besides, we also need another estimation according to the result of spectrum around this spectrum. That is, if we get the preliminary result $y_{i,j}$, i is the ith unit of azimuth and j is the jth unit of slant. The final result $y_{i,j}$ should be as follows:

$$y_{i,j} = (1-w)y_{i,j} + \frac{w(y_{i-1,j} + y_{i+1,j} + y_{i,j-1} + y_{i,j+1})}{4} \tag{3-1}$$

w is the weight that surrounding spectrum data affect the result.

3.2.2 Algorithm Setup

Training

In our problem, there are several variabilities for different radar configure. The range of Doppler frequency may be -5Hz to 5Hz or -20Hz to 20Hz. So we train the data at different frequencies separately. Besides, for data on the same frequency, we also divide them to two conditions, one is that all the data are sea clutters, the other one is the junction of the sea. It is not easy to label the data unionizing sea and land accurately. So we only choose the data we can ensure that it is sea/land. Of course, to guarantee the diversity of samples, we choose lots of data in different conditions.

Evaluation

As a classification problem, the usual way to evaluate is the percentage of satisfactory results. However, in our problem, as described above, the data near the border of sea and land are difficult to classify. These parts also play an important role in our question. So we add another parameter to evaluate our algorithms rather than only correct rate. We compare the area of our predication results with the real geographical zones. Thus we can get

$$g_{C_1,C_2} = \frac{area(C_1 \cap C_2)}{max(area(C_1), area(C_2))} \tag{3-2}$$

$area(C)$ represents the area of zone C, we use 0 and 1 in our binary image, g_{C_1,C_2} shows the similarity of C_1 and C_2 as shown in figure 3-1.

Baseline

We compare the performance of our algorithms and a naive baseline of simply calculating only one main feature of the spectrum data. Usually, most differences between sea and land clutter are that the frequency for the maximum energy is almost zero. However, there are two similar peaks in sea clutter symmetrically along the zero frequency which are called Bragg peak. Thus, we can use the frequency f to identify the sea/land.

$$f_{i,j} = \arg\max_{f} \quad x(i,j,f) \tag{3-3}$$

图 3-1: A binary map.

$x(i,j,f)$ is the energy at frequency $f_{i,j}$. As we get $f_{i,j}$, we need to compare it with the threshold η.

$$y_{i,j} = \begin{cases} 0 & |f_{i,j}| > \eta, \\ 1 & |f_{i,j}| < \eta \end{cases}$$

0 represents the sea and 1 represents the land.

3.2.3 Our Classification Algorithm

A typical convolution neural network consists of a number of different layers stacked together by a deep structure: an input layer, multiple sets of convolution and pooling layers, a finite number of fully connected hidden layers, and an output layer.

The convolution layer introduces a special way of organizing a hidden element whose purpose is to take advantage of the local structure that exists in the input data. Each hidden unit is not connected to all inputs from the upper layer and is limited to only a small portion of the entire input space (for example, a small $1*3$ block). The weight of this hidden unit creates a convolution kernel, which is applied to the entire input space, resulting in feature maps. In this approach, you can reuse a set of weights for the entire input space. This is based on the premise that local useful features are also useful in other locations in the input space, which not only greatly reduces the number of parameters to be estimated, but also improves the translation invariance of the data.

Based on the actual data of our sea/land clutter spectrum and the characteristics it reflects, we construct a basic convolution neural network with six layers as shown in figure 3-2, each layer has multiple eigenvectors, each eigenvector has multiple neurons,

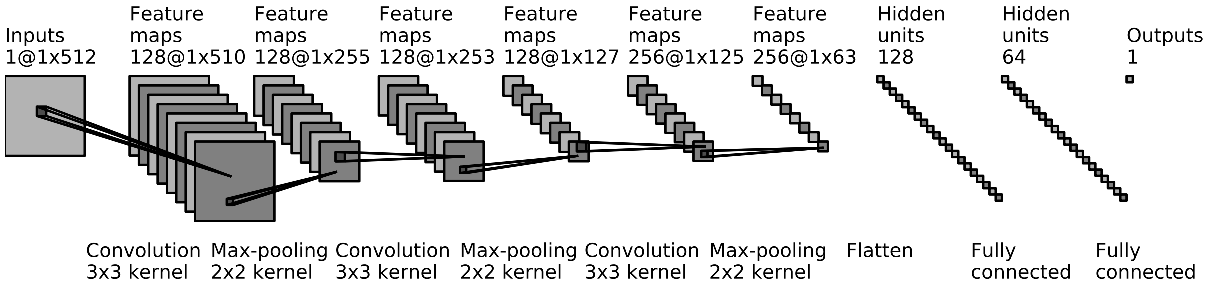


图 3-2: The structure of our convolution neural network.

and each eigenvector is derived from a feature of the convolution filter that extracts an input.

Step 1: Input our sea/land clutter spectral sequence (a sequence of $1 * 512$ in size) and convolve it to obtain the C1 layer. In this case, 32 neurons with a size of $1 * 3$ are used, so that each neuron in the eigenvector is connected to the $1 * 3$ neighborhood in the input, so that the feature size in the C1 layer is $1 * 510$. There are 156 trained parameters (each filter has 3 cell parameters and a bias parameter, a total of 32 filters, total $(1 * 3 + 1) * 32 = 128$ parameters), a total of $128 * (1 * 510) = 65280$ connections will be connected via the ReLU active layer.

Step 2: We apply a maximum pooling(the length is 2) process to C1 layer. The operation replaces the two adjacent features with one feature, which can help reduce the length of the feature vector, the amount of computation, and the over-fitting problem.

Step 3: After the above two steps of operation, we are equivalent to regain a new eigenvector, with this feature vector as input, repeating steps 1-2 twice, we can get a three-stage convolution neural network structure. Through the multi-stage convolution operation, the features of input vectors are fully extracted. Then, for the feature vector, flatten operation, as a convolution layer to the full connection layer of a transition, in the whole connection layer on the basis of adding dropout parameters, and then add a second layer of the whole connection, through the activation function Sigmoid. The structure of our algorithm is constructed.

Step 4: Optimize the training of our neural network model. After building a CNN model, we need to do further training on the model.

Step 5: Predictive steps. Depending on step 4, we can get the training model. In the forecasting step, we use a sliding window method to pre-process the input data. We take the same wave multi-shot window length multi-frame spectrum data averaging, as a new input to offset some interference and frequency shift.

Pooling Layer

After we have acquired the features by convolution, the next step is to use these features to do the classification. In theory, people can use all the extracted features to train the classifier, such as the softmax classifier, but this is faced with the challenge of too many eigenvectors to calculate and easily leading to over-fitting.

Because our clutter spectrum data have a static attribute, it means that the useful features in a data region are likely to be equally applicable in another region, the convolution feature can be used. Thus, in order to describe data with a large amount of data, a natural idea is to aggregate statistics for different locations, for example, one can calculate the maximum(or average) of a particular feature on an area of the sequence. These summary statistical features not only have a much lower dimension(compared to the use of all extracted features), but also improve the results(not easy to over-fitting). This aggregation is called pooling, and the commonly used pooling methods are average pooling and maximum pooling.

These pooling units have translation invariant if the continuous range in the spectral vector is chosen as the pooled region and only the characteristics of the same (repeating) hidden cells are pooled. This means that even if the spectral vector undergoes a small translation, it will still produce the same (pooled) feature. That is, in our problem, this can be a good deal when the Bragg peaks shift.

Formally, after obtaining the convolution features we discussed earlier, we pooled our convolution features based on the selected pooling length. We use the maximum pool, that is, select the largest value as the features of this pooling unit after the follow-up classification.

Activate Function

The choice of activation function is a very important aspect of this problem. The traditional methods usually choose Sigmod or hyperbolic tangent. However, we generally use the following ReLU activation function in the convolution neural networks.

$$F(x) = max(0, x) \tag{3-4}$$

ReLU has several advantages over traditional activate function: faster calculations and more efficient gradient propagation(they are not saturated like S-shaped units), biological likelihood and sparse activation structures while still retaining sufficient discriminate nature despite their simplicity. One of its shortcomings is the initial state of the random weights, and multiple units may fall prematurely into the dead zone(a constant gradient of zero output). However, when connecting with the whole connection layer, a Sigmod activate function is better.

$$F(x) = \frac{1}{1 - exp(x)} \tag{3-5}$$

Dropout Parameter Learning

All convolution neural network structures have a tendency to over-fit, although the number of parameters can be reduced by weight sharing. In our problems, the number of training cases is larger than an order of magnitude of evaluation cases. This may lead to the generalization beyond the scope of the sample. Therefore, we can use a simple but efficient concept, dropout, to improve the training model. In each training iteration, each concealment unit is randomly deleted with a predetermined probability, and the learning process continues normally. These random perturbations effectively prevent the network from learning fake dependencies and create complex common adaptations between hidden cells. Such a large number of neurons not only become useful in the context of other neurons. The architectural average introduced by dropout attempts to ensure that each hidden unit learning is usually conducive to generating a feature representation of the correct classification answer.

Optimization method

The traditional neural network selection method is mini-batch gradient descent. The idea is to calculate the gradient of mini-batch for each iteration, and then update the parameters. However, this method has two shortcomings, one is that the choice of learning rate is difficult because of its use of the same learning rate for all parameters, the other one is that it tends to converge to a local optimum.

In this paper, we choose an adaptive algorithm, Adaptive Moment Estimation, which has an adaptive learning rate that dynamically adjusts the learning rate of each parameter by using the first-order moment estimation and the second-order moment estimation of the gradient. After the correction, each iterative learning rate has a clear range, making the parameters more stable.

3.2.4 Datasets and Analysis

All the data we have are spectrum data in different days, different places and different radar configurations. We look over all the spectrum data and select some typical spectrum data as shown in figure **??**.

Dataset Grouping

In our problem, when the radar configuration changes, we may get spectrum data in a different frequency range and accuracy. For example, some data have 512 coherent accumulation points ranging from -5Hz to 5Hz and some have 256 points from -10Hz to 10Hz. Therefore, we divide all data to 4 groups:

- Group A: There are 256 points from -10Hz to 10Hz shown in figure **??**;
- Group B: There are 512 points from -5Hz to 5Hz shown in figure **??**;
- Group C: There are 512 points from -10Hz to 10Hz shown in figure **??**;
- Group D: There are 1024 points from -5Hz to 5Hz shown in figure **??**;

We only choose these four typical groups and give up other groups similar to them, such as data with 512 points from -10Hz to 10Hz which is similar to group B.

3.3 Sea/Land Classification Evaluation

In this section, we evaluate the performance of the model presented before.

3.3.1 Algorithm Implementation

We compare our algorithms with two other algorithms, traditional single feature recognition algorithms and SVM algorithms. Three characteristics of sea/land clutter selected for SVM are:

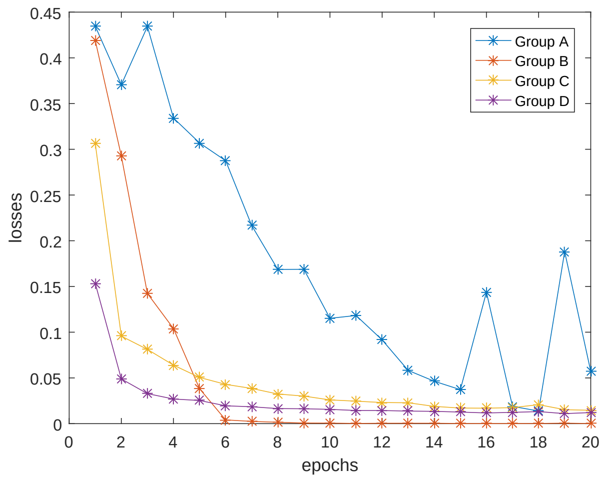


图 3-3: The losses for different dataset groups.

- Maximum backscatter amplitude
- The difference between the maximum and second major frequency in the spectrum
- The difference between the maximum and the second largest amplitude in the spectrum

To ensure that we have enough data to train and test our algorithm, we consider several frame data(there are about 20000 spectrum data for every frame) in different conditions. We also randomly select 70% of data as training data, 10 percent is used as validation data and others are test data. As described before, the area ratio is used for evaluate the data near the border of sea and land.

3.3.2 Overall Quality

In order to test the universality of our algorithm, we test our method, SVM and the baseline algorithm in four groups dataset as described preceding section shown in figure 3-3. Figure 3-3 shows our algorithm can have a good results in different dataset groups. Although, for the same neural network structure, the first dataset group converges in the largest epoch times. This is because that there is less information or features when the ratio of frequency and points goes smaller.

As we described before, there are another two usual methods to solve our problem. We did some experiments to combine our algorithm with them. Table 3-1 shows the correct rate and matching rate. Our method meets the best result in both experiments.

表 3-1: Correct and matching rate comparing of three methods.

	Our method	SVM	Baseline
Correct Rate	99.69%	92.44%	81.85%
Largest Matching Rate	88.99%	22.77%	23.48%
Matching Rate	88.99%	81.31%	88.21%

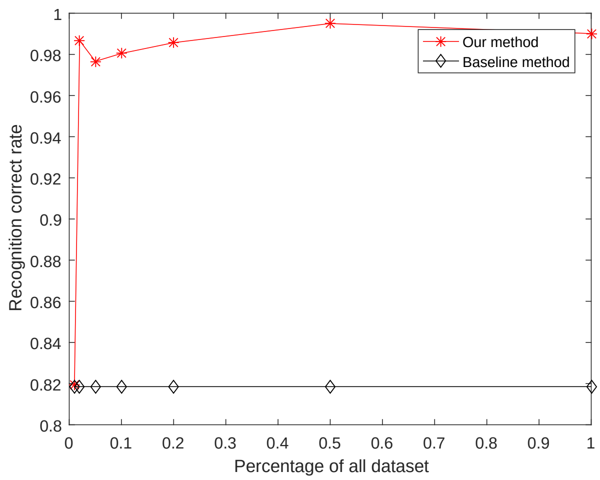


图 3-4: The experiments of comparing our method and baseline method against sample sizes of dataset.

Besides, when finding the largest matching rate through the whole world map, the mating rates for the three methods to their paired maps in some time seem to differ a little. However, we can find that both SVM and baseline method pair to wrong zones.

Figure 3-4 shows the average classification accuracy rate for different sample sizes. As the baseline method only uses a threshold got according to prior knowledge, it differs a little as the dataset grows. Our learning method has a better result as the data volume increases. As we all know that parameters of convolution neural network play an important role in classification correct rate. Therefore, we first do some experiments to show the accuracy of validation data when epoch and batch differs. In fig 3-5, we can easily see that the accuracy grows along with increasing of epoch times. Besides, larger is the batch, easier it is to converge. As we described before, we use a fusion method to avoid the saltation change in spectrum sequence. Figure 3-6 shows that the matching

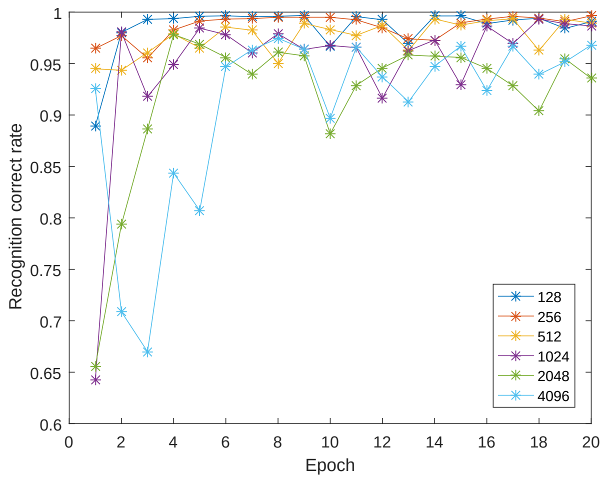


图 3-5: Validation accuracy against epochs for different batches.

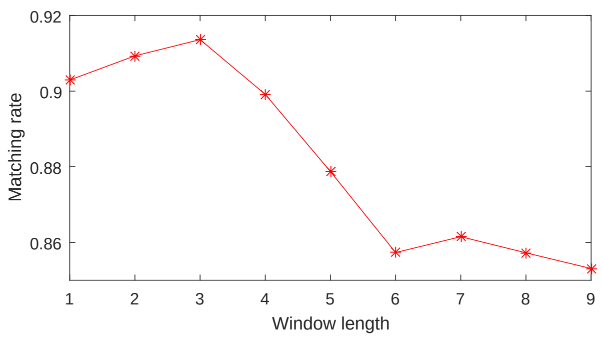


图 3-6: The matching rate against fusion window length.

rate grows as the window length increases at first, and then it decreases. To find the best threshold to distinguish sea/land result, we calculate the correct rate of the same test data using different probability threshold. Figure 3-7 shows that rate increases as the threshold is larger and the growth rate becomes slower. In the other aspect, when the threshold is only 0.01, the recognition rate is still higher than 0.86. The probabilities of recognition our method are mostly convincing as shown in 3-8.

3.3.3 Feature Visualization

There is a problem for the CNN method is that we cannot estimate the feature we learn intuitively. Therefore, in this section, we use a gradient-based visualization method to show the support feature for the result using our trained model. We define a sequence of our spectrum data as$S = \{s_1, s_2, .., s_n\}$, where n is the number of points in

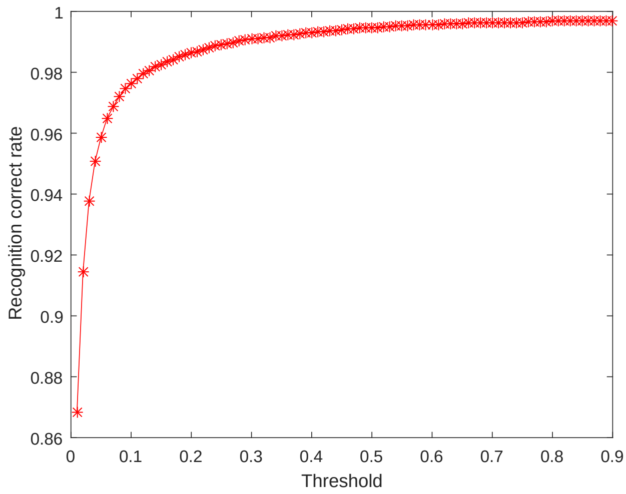


图 3-7: The recognition correct rate against the threshold.

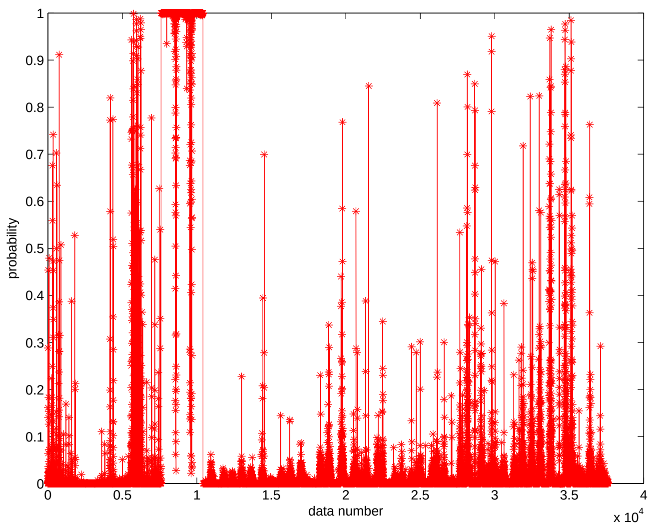


图 3-8: The recognition correct rate against the data number.

the sequence, and our output probability $p(S)$. Thus, we can get:

$$p(S) = w^T S + b, \tag{3-6}$$

where w and b are respectively the weight and bias of our model. In fact, the weight w here shows the importance of corresponding points. In our model, the class probability function $p(S)$ is a highly non-linear function, a Taylor method is used here to approximate $p(S)$. To simplify the calculation, we use first-order Taylor expansion:

$$w = \frac{\partial p}{\partial S}|_{s_i} \tag{3-7}$$

图 3-9: The heat map for features that play import roles.

Therefore, we can get the w in equation 3-7 can be calculated by back-propagation, which is not needed to describe clearly. Figure 3-9 shows that the features mainly focus on the data as we have expected.

3.4 Conclusion and Future Works

In this paper, the sea/land clutter identification problem of OTHR target localization accuracy is proposed in a novel algorithm based on convolution neural network. The traditional threshold recognition method or SVM algorithm extracts the features from spectrum data according to the experience, which leads to the operation complexity and the low classification precision. The CNN-based sea/land recognition method does not have the above shortcomings.

In this paper, our algorithm is compared with the traditional algorithm and SVM algorithm. The experiments show that our method is efficient and reliable in the sea/land identification problem. With the help of the classification results, we can get a precise correction factor for our target tracking problem.

3.4.1 Future works

In this paper, we have tested and verified the effectiveness of our convolution neural network sea/land recolonization method. There are still some further studies of the workplace:

- In addition to our convolution neural network structure, we can try other neural networks(i.e. RNN, which is a usual method for time series data) or build a CNN with other structures.
- We now divided our data into several groups and train them separately. We can try to use some methods to fusion these data and generate a model that can fit in every problem.
- We also intend to perform unsupervised algorithms to unlabeled data to pre-train the networks.

4 基于深度学习的辐射源未知分类识别

4.1 引言

在跟踪发达国家研究进展的基础上，国内也开始加紧研发可装备于军方的 SEI 系统，以逐步缩小与发达国家在技术实用方面的差距。但总体来说，我国在该方面的研究还赶不上美英等发达国家，除了缺乏深层次且系统化的理论分析研究外，更缺乏成熟的工程化系统实践和实际装备，因而迫切需要加快在该领域的理论研究和应用步伐。本文综合雷达信号处理、深度学习等多学科理论，重点围绕在复杂电磁环境下不同辐射源的个体识别所面临的识别能力差等问题与挑战，提出合理的雷达脉内细微特征模型，结合深度学习的理论与方法，解决传统辐射源识别方法的局限性，为雷达辐射源识别提供理论支撑于技术指导

Open Set 目标识别系统必须可以准确的处理下面三种类型的数据类：

- 已知的（目标）类，被标记为正面训练样本的数据。
- 已知的未知（非目标）类，被标记为负面训练样本的数据。
- 未知的未知（非目标）类，在训练样本中不存在的类别的数据。

国内外对于 Open Set 的识别也早有研究，Simonson 提出了一种称作 probabilistic fusion (PF) 的利用统计的方法来进行 Open Set 识别，其主要通过合并来自不同数据源的证据得到一个统计测试模型，根据此模型的分布来对于类别进行判断。Scheirer 等人提出了一种通过分析后验数据得分来进行类型判断的方法。

4.2 辐射源信号分析

对于辐射源信号的处理，本文主要考虑两方面：信号预处理、特征提取优化。

在信号预处理方面，首先需要剔除无用和错误的数据。然后将信号进行分选，其主要是从随机交叠的脉冲信号流中分离出各个雷达的脉冲信号并选出有用信号。其实质是去交叠、去交错，所利用的是同一部雷达信号参数的相关性和不同雷达信号参数的差异性。

在特征提取优化方面，合理的特征是分类识别的基础。本文以模糊函数为平台，分析提取其切片特征。

4.2.1 模糊函数

模糊函数不仅能描述雷达信号的分辨特性和模糊度，还能描述由雷达信号所决定的测量精度和杂波抑制特性等，并根据这种雷达无意调制产生的信号脉内细微特征来进行分类所需的特征。对于信号 $x(t)$，其瞬时自相关函数为 $R_x(t,\tau)=x(t+\tau/2)x^*(t-\tau/2)$，其中 τ 为时延，模糊函数的定义为，

$$A(\tau,\nu)=\int_{-\infty}^{+\infty}R_x(t,\tau)e^{j2\pi\nu t}dt \tag{4-1}$$

即 $R_x(t,\tau)$ 关于时间 t 的傅里叶反变换。由于在实际中发射机自身存在相位噪声以及各类杂散输出，故可以区分出型号、参数均相同的辐射源，通过模糊函数在时延和频偏这二维上的变换，可以多角度的刻画出无意调制对于发射信号的影响。

为了方便在数字信号中使用，上式可以经过变换等价于下面的形式：

$$A(\tau,\nu)=\int_{0}^{\tau}x(t)x^*(t+\tau)e^{j2\pi\nu t}dt \tag{4-2}$$

对信号均匀采样，即对接收信号和参考信号离散化后，上式可以表示为：

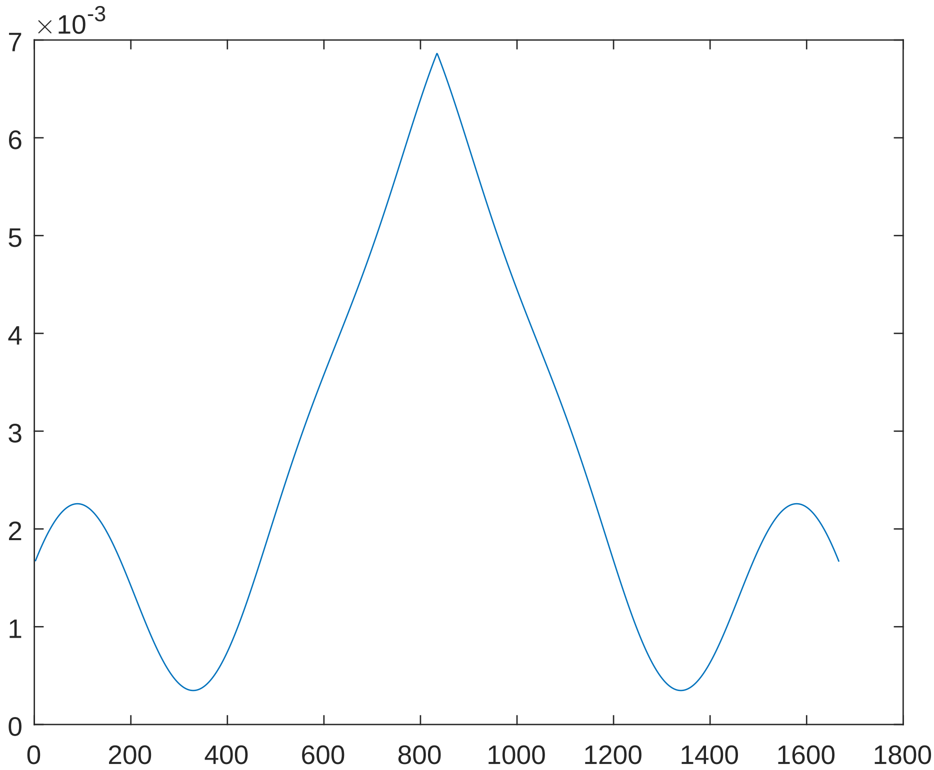
$$A(\tau_l,\nu_m)=A(l,m)=\sum_{n=0}^{N-1}x(n)x^*(n+l)e^{\frac{j2\pi mn}{N}} \tag{4-3}$$

其中，$\tau_l=l/f_s$,$\nu_m=mf_s/N$。

4.3 Open Set 分类器设计

此部分主要解决的问题是当得到一个新的测试样本，如果该样本不属于已经经过训练的分类，那么传统的神经网络模型会将该样本指派给与其最相似的一个类别，此种情况对于一个 Open Set 识别系统，也即类似于辐射源识别系统这种具有较多尚未经过训练的样本的一个数据集，首先这会导致其识别率下降，另一方面是由于对于未知的辐射源无法很好的确定，无法很好的完成预警等任务。国内外学者对于该问题的研究主要分为下面两个思路：

- 在训练集中添加一个“未知”类别，利用不同的来自非已知类别的数据作为训练样本对该类别进行训练，然后对于所有的输入数据进行类别的识别，对于识别结果为该类别的数据作为未知分类。然而该思路最大的问题是我们无法得到所有可能的未知类别的样本来进行训练，具有一定的局限性。
- 针对于多分类使用的 softmax 函数，可以设立阈值或者对于该识别结果进行一个评价（例如与已知类别数据的一个“距离”）等进行分辨出未知的分类。



×10^-3
7
6
5
4
3
2
1
0
0
200
400
600
800
1000
1200
1400
1600
1800

针对于该问题，我们基于思路 2 的想法设计了一个基于 meta-recognition 的可以识别未知辐射源的深度神经网络。首先是创建一个深度卷积神经网络分类器，该分类器的输出为该训练样本属于各个类别的概率，我们然后将此类别作为一个输入，输入到我们的 meta-recognition 中，这里我们设计一个支持向量机分类器作为 meta-recognition，然后从该 meta-recognition 会进行判断该输入是否为一个未知分类。

4.3.1 深度卷积神经网络分类器设计

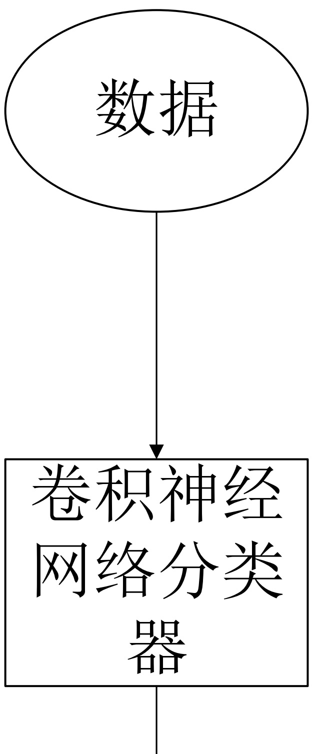
在分类器设计方面，本文设计利用卷积神经网络的分类器。典型的卷积神经网络由深层结构堆叠在一起的多个不同的层组成：输入层，多组卷积和池化层，有限数量的完全连接的隐藏层，以及输出层。其中最主要的部分为卷积层。其利用输入数据中的局部结构，将整个输入空间划分成很小的隐藏单元。将各个隐藏单元的权重构建得到的卷积核作用于整个输入空间，从而得到特征向量。利用这种机制，我们不仅大大减少了参数数量同时提高了数据的平移不变性。据辐射源信号的实际数据以及其反映出来的特性，构建了基本的具有 13 层的卷积神经网络，每层具有多个特征向量，每个特征向量具有多个神经元，并且每个特征向量来自于一种卷积核所提取输入的一种特征。主要过程为对于输入的辐射源信号，进行多次的卷积、池化操作，进行再次特征提取，然后通过 BP 网络进行训练。

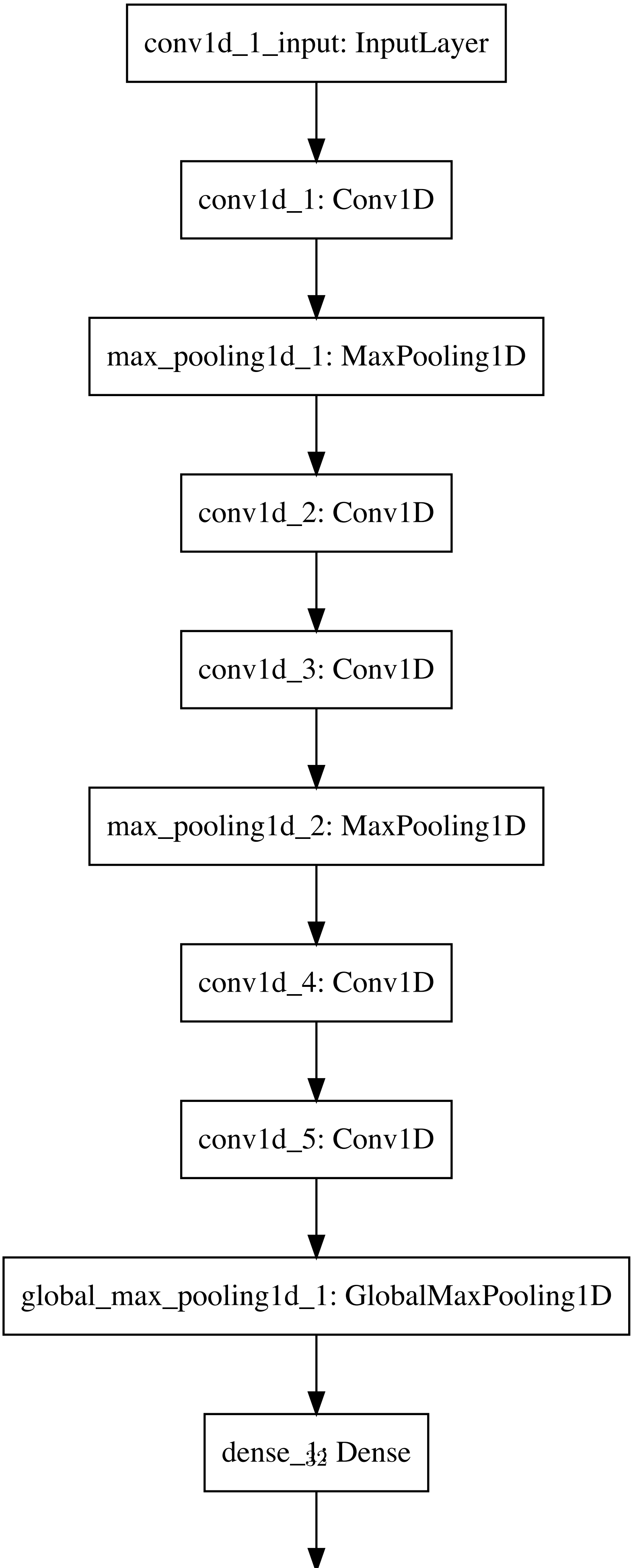
4.4 SVM meta-recognition 设计

支持向量机是一种流行的分类方法，因为它们可以在不需要大量数据的情况下产生良好的结果。我们可以利用所有的目标数据和未知目标的数据来作为训练样本对该 SVM 分类器进行训练，本部分我们以深度卷积神经网络的输出作为该分类器的输入，利用各类别的概率作为其特征进行训练识别。由于在类别的识别过程中，存在一定的波动性，这个会影响对于是否属于未知类别的分类判断，我们这里选取对于来自同一个辐射源的连续 10 拍的识别结果进行一个平均作为最终的输入。

下面是对于 SVM 分类器的设计，首先是核函数的选择。核函数将输入空间映射到高维特征空间，最终在高维特征空间中构造出最优分离超平面，从而把平面上本身不好分的非线性数据分开。常用的核函数为线性核函数和高斯核函数。对于核函数的选择，一般分为三种情况：

- Feature 的数量很大，跟样本数量差不多，这时候选用 LR 或者是 Linear Kernel 的 SVM


数据
卷积神经网络分类器


conv1d_1_input: InputLayer
conv1d_1: Conv1D
max_pooling1d_1: MaxPooling1D
conv1d_2: Conv1D
conv1d_3: Conv1D
max_pooling1d_2: MaxPooling1D
conv1d_4: Conv1D
conv1d_5: Conv1D
global_max_pooling1d_1: GlobalMaxPooling1D
dense_1: Dense

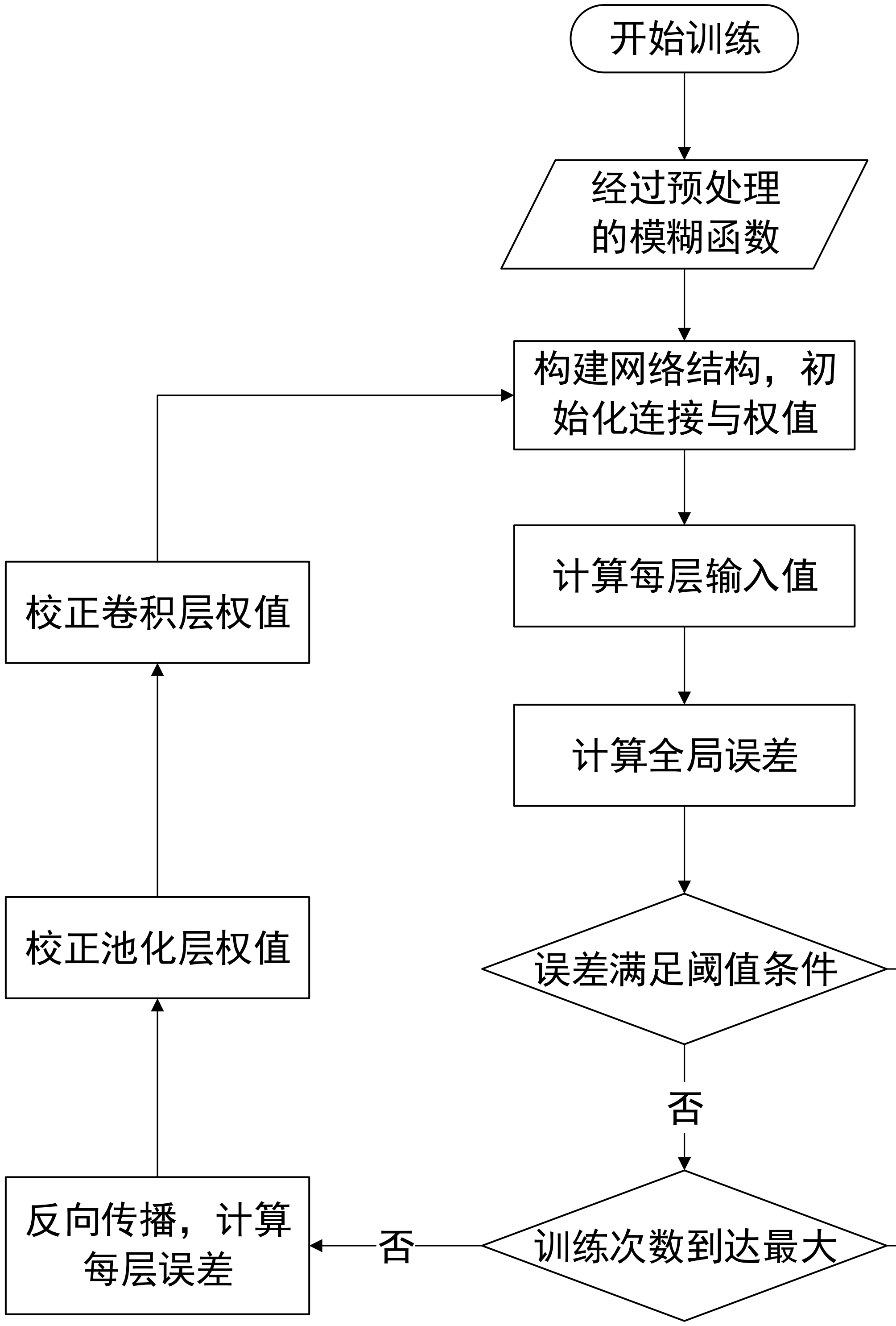


图 4-4: 深度卷积神经网络算法流程图

- Feature 的数量比较小，样本数量一般，不算大也不算小，选用 SVM+Gaussian Kernel

- Feature 的数量比较小，而样本数量很多，需要手工添加一些 feature 变成第一种情况

由于我们的问题符合情况 2，故选择高斯核函数。

支持向量机具有两个关键参数，惩罚参数 C 的和核参数 σ，这两个参数的取值在很大程度上决定了 SVM 的性能的优劣。核函数的参数主要影响样本数据在高维特征空间中分布的复杂程度, 即维数。特征子空间的维数越高, 那么得到的最优分类超平面就会越复杂。反之亦然。因此只有选择合适的核参数得到合适的特征子空间, 才能得到推广能力良好的 SVM 分类器。本文中用到的是高斯核参数。大量的实验数据表明，如果与样本点之间的距离很小，$\sigma \to 0$；如果与样本点之间的距离很大时，$\sigma \to \infty$；当 σ 很小，高斯核函数支持向量机得到的判别函数差不多是一个常数，出现过拟合现象。当 σ 很大时，样本的正确分类率也会比较低。

惩罚参数是影响 SVM 算法性能的另一个重要因素。它的作用主要是调节特征子空间中 SVM 模型的置信范围与经验风险的比例，使支持向量机的泛化能力达到最好。特征子空间不同时，最优参数值取值也会不同。惩罚参数与经验误差的惩罚和 SVM 的复杂度成正比，与经验风险值成反比，反之亦然。因此，选择合适的惩罚参数也是非常重要的。

从上面的分析可以看出, 核参数影响着映射函数、进而影响样本子空间的复杂度。最后会影响分类机性能的好坏。惩罚参数作用是在数据子空间中调节学习机器自信区间的范围。这些都说明了惩罚参数和核参数的选择非常重要。

4.5 仿真实验与分析

4.5.1 实验环境

由于我们原始获得的数据为 IQ 两路数据，为了更好的捕捉到回波的特征信息，我们对数据进行了一个变换，求取其模糊函数，并做偏移为 0 附件的一个切片。由于深度学习需要大量的数据进行训练学习，而本身数据量偏少，故我们在已有数据的基础上在一定信噪比的前提下，生成部分仿真数据。

对于数据的选择方面，我们从数据中选择出 2 至 8 个类别分别进行实验，对于每一个类别，我们均选择大约 10000 组数据，其中 70% 作为训练样本，20% 作为交叉验

证样本，10% 作为测试样本，同时在测试样本中又添加了与已知分类等数量的未知分类的数据进行测试。

由于该变换后，数据之间的差距比较大，我们对数据进行了归一化。我们采用的归一化方法为 min-max 标准化（Min-Max Normalization），也称为离差标准化，是对原始数据的线性变换，使结果值映射到 [0 , 1] 之间。转换函数如下：

$$x^* = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{4-4}$$

其中 x_{max} 为样本数据的最大值，x_{min} 为样本数据的最小值。

我们采用网格搜索法对 SVM 参数进行调优，最终选择参数惩罚参数为 32，核参数 σ 为 0.0312。

4.5.2 实验结果分析

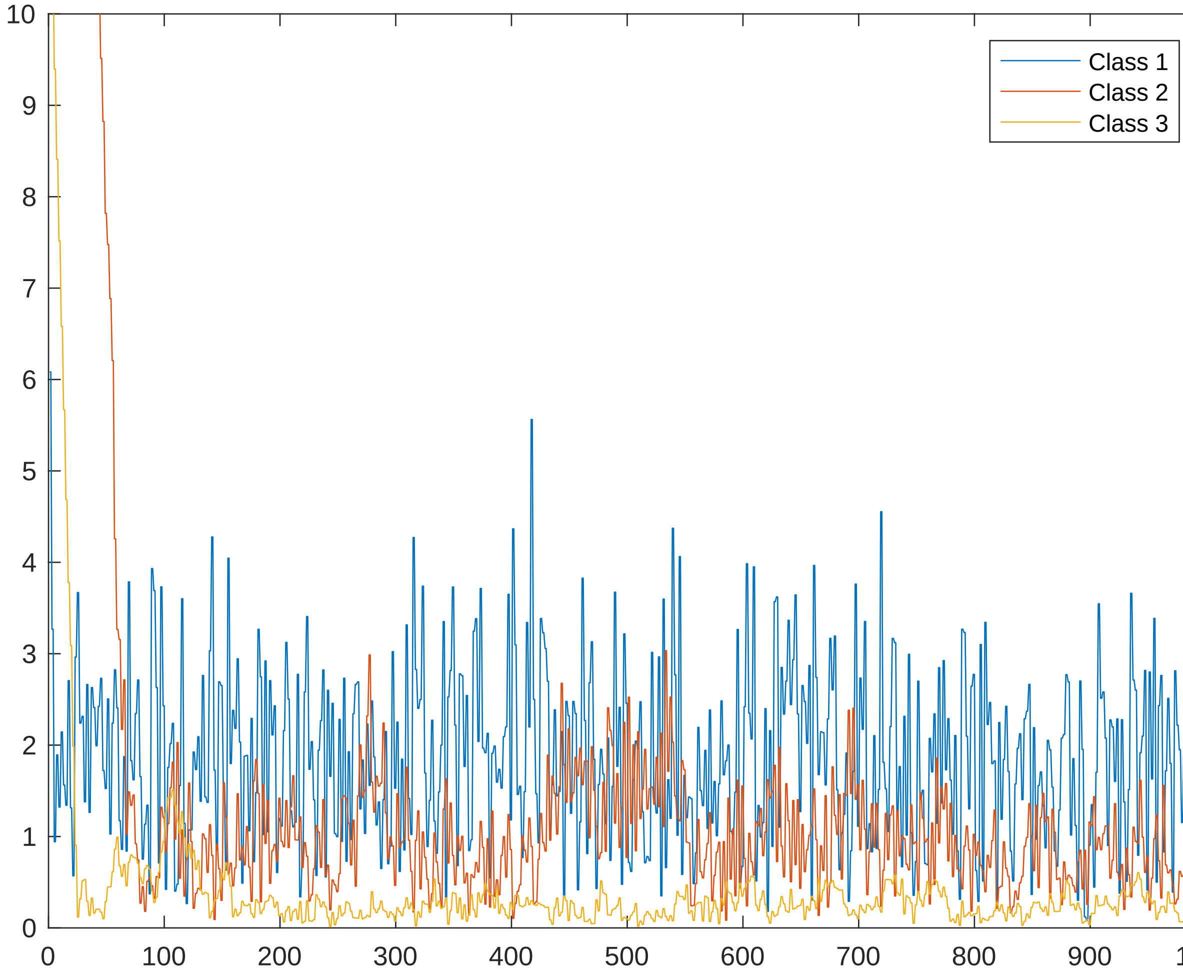
在上述样本的情形下，我们通过选取不同的类别数目，进行训练和测试得到下表的识别结果。从表中数据我们可以看出，随着样本类别数的增加，对于未知分类的识别准确率也随之有了大幅度的增加，而另一方面随着类别的增加，对于每个类别的识别准确率有一定的降低，但是仍然维持在比较高的水平。

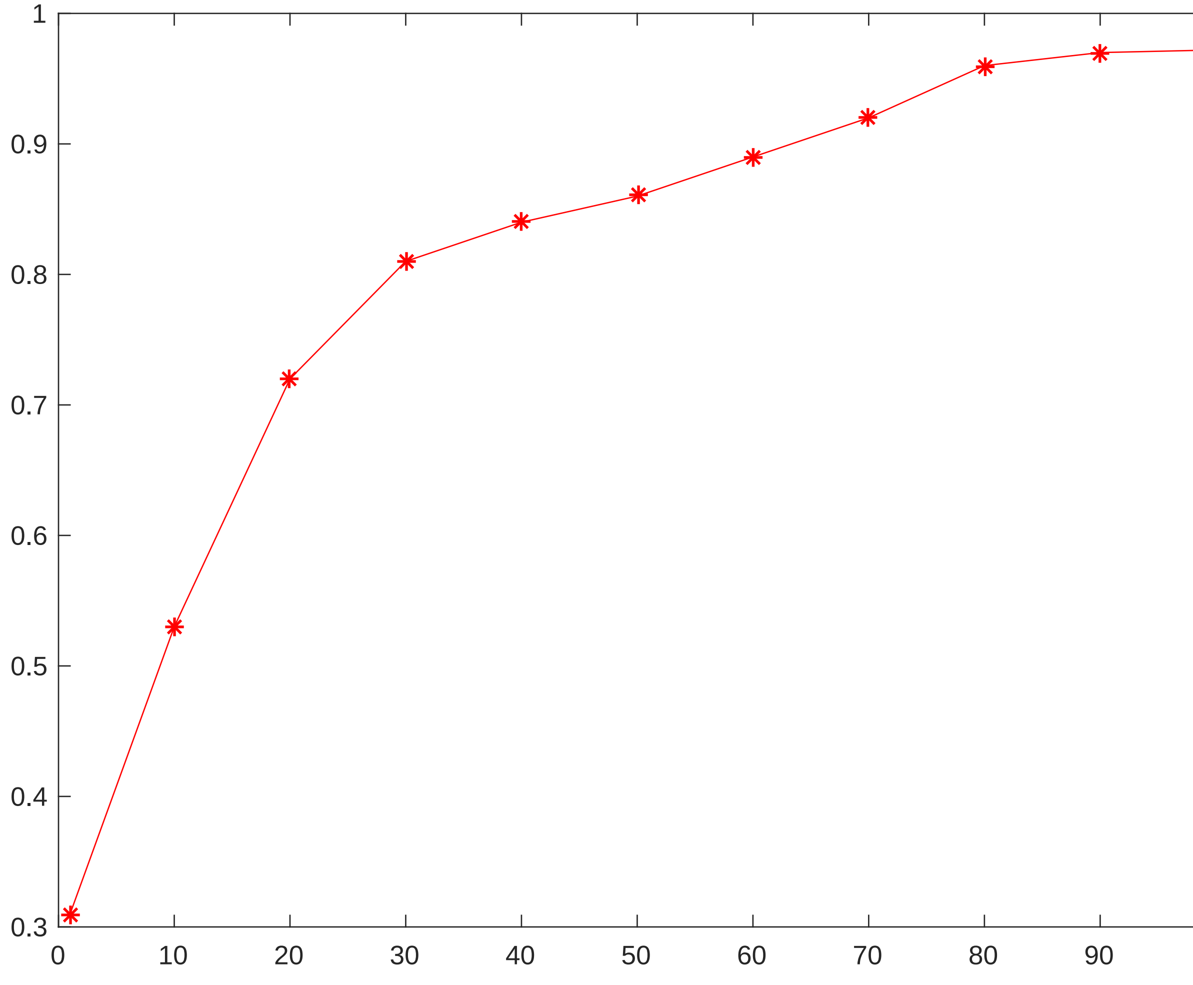
4.6 结束语

本文针对复杂电磁环境下辐射源的识别面临的电磁信号干扰大、雷达信号参数相近等问题与挑战，利用深度学习的思想与方法，深入研究辐射源脉内细微特征，设计合适的神经网络结构，并基于实际机载气象雷达数据进行初步验证。主要特色与创新点如下：

（1）利用深度学习方法进行辐射源识别前沿。通过对现有辐射源信号进行分析，利用其脉内细微特征作为训练样本，使得识别准确率有了较大的进步。虽然已有研究利用神经网络、支持向量机等机器学习算法进行识别，但是仍然需要基于雷达信号的基本参数，没有考虑信号的内部特征参数。

（2）本文采用方法具有较强的抗噪声、抗干扰能力。传统方法进行辐射源个体识别前均需进行降噪、多径抑制和分选等复杂的信号预处理工作，这些操作会在一定程度上削弱雷达的个体特征。深度学习方法可以通过大量的样本，智能地判断各特征的权重，通过赋予不同的权重在保留雷达个体特征的情况下，避免干扰的影响。由此可见，本文所运用的方法具有较好的鲁棒性。


Class 1
Class 2
Class 3
0
1
2
3
4
5
6
7
8
9
10
0
100
200
300
400
500
600
700
800
900


1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0
10
20
30
40
50
60
70
80
90

我们希望未来在目前的基础上，在下面几方面做进一步的研究：（1）利用更多的数据对算法进行进一步的验证，目前类别较少的情况下，部分结果会对选择的类别具有一定的依赖性，另一方面是选取更多更合适的特征进行训练学习；（2）利用集成学习提高学习精度；（3）尝试新方法对于未知分类识别；（4）对于未知分类，尝试利用无监督或者半监督学习进行训练学习。

5 总结

5.1 本文的主要贡献

5.2 后续的研究进展

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附录

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攻读博士学位期间发表的学术论文和参加科研情况

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