**Introduction**

**(晶粒尺寸的重要性)**The measurement of grain size plays an important role in the research of metal materials. Information related to material properties, such as yield strength, tensile strength, elongation, etc. can be obtained, which has an important impact on material properties. The traditional methods of grain measurement rely on manual operation, which is time-consuming and prone to errors. In the analysis of metal microstructure, the information of grain boundary, grain size and grain distribution can be obtained by image analysis, and these parameters can be estimated by automatic methods of image processing and mathematical morphology. (商用软件)Currently, there are some commonly commercial software for grain size rating, such as image-pro Plus, Image Tool, Image J, etc. To some extent, these tools reduce the manual work and improve the analysis efficiency. However, the operation is tedious and the scope of application is too narrow to be competent for the analysis of complex images, with fuzzy boundary or much noise. Meanwhile, commercial software has a very high cost. (现有技术) There are also many methods to contribute to extraction of grain boundary and grain size rating. Jiang et al. used the multi-scale geodesic extension algorithm to restore and reconstruct grain boundaries based on the improved extension definition. Deng et al. proposed a closed edge extraction algorithm for metallographic structure based on Canny algorithm and gray contour. Park and Yu Ding et al. used convex analysis to divide the conforming boundary into individual components, and used the missing value estimation based on FPCA (function principal component analysis) to recover the missing boundary components. Orhan Dengiz et al. used neural network and fuzzy logic algorithm to detect the boundary of the alloy. Lauch Lukasz et al. used the feedback pulse coupled neural network to optimize the bionic algorithm to achieve part of the microstructure image. These methods have made important contributions to the measurement of grain size and grain segmentation, but they are not effective in dealing with problems such as fuzzy boundary, high noise and poor picture quality.

(**本文贡献**)In this paper，based on the microscopic image of 690 alloy and the mixed image data, a method to automatically measure the grain size of 690 alloy is introduced. After the preliminary pretreatment of metallographic image, the grain segmentation was carried out, and the discontinuous grain boundary was reconstructed and completely segmented by the method of deep learning, so as to explore the reliability of boundary extraction.

**（晶粒尺寸的重要性）晶粒尺寸的测量在金属材料的研究中有着重要的地位，可以得到与材料性能有关的信息，如屈服强度，抗拉强度，延伸率等，而这些信息对材料的性能有着重要的影响。传统的晶粒测量方法依赖于手工操作，耗时长，而且极易出错。随着计算机技术和图像处理技术的发展，晶粒度测量技术已经有了明显的改善。在金属微观结构分析中，可以通过图像分析得到晶界、晶粒大小和晶粒分布的信息，并通过图像处理和数学形态学的自动方法对这些参数进行估计。（现在技术有所发展，商用软件，常用方法）目前有一些常用的商用软件如Image-pro Plus, Image Tool, Image J等，虽然这些工具在一定程度上减少了人工工作量，提高了分析效率，但是操作繁琐，而且适用范围太窄，不能胜任对于边界模糊，噪音多的复杂图像的分析。并且商业软件不能够量身定做，成本较高。现在也有很多的方法对此做了贡献。Jiang等人基于改进的扩展定义，使用多尺度测地线扩展算法来恢复和重建晶界。Deng等人提出了一种基于Canny算法和灰度轮廓线的金相组织闭合边缘提取算法。Park和Yu Ding等使用凸分析将符合边界划分为单独的分量，并使用基于FPCA（function principal component analysis）的缺失值估计来恢复边界缺失分量。Dengiz等人采用神经网和模糊逻辑算法对合金的边界进行检测。劳赫 Lukasz 等人利用反馈脉冲耦合神经网络优化仿生算法实现了部分微观结构图像。以上这些方法对于晶粒分割和晶粒尺寸的测量做出了重要的贡献，但是应对边界模糊，噪声大，图片质量差等问题，没有很好的效果。**

**（本文的贡献）本文基于690合金的微观显微图像以及复杂混合多样的图像数据混合，经过大量的实验，提出了基于深度学习的晶粒尺寸的测量方法。对金相图像做初步的预处理之后，进行晶粒分割，使用深度学习的方法对不连续晶界进行重构，完整分割，进而探讨境界提取的可靠性。**

**Related Work**

At present, many researchers have done a lot of theoretical and experimental research on grain boundary extraction and made remarkable progress. Now，the mainstream of the research ideas are mainly divided into two directions [12]. One is to segment the grains in the metallographic image in order to obtain a complete grain. Grain boundaries are adjacent to each other. The main methods are: watershed segmentation algorithm [13] [14], level set segmentation algorithm, clustering segmentation algorithm, etc. Secondly, some operators are used to extract grain boundaries directly from metallographic images, such as canny operator [15], Sobel operator [16] and kirsch operator. For the first research idea, the main research focus is the grain in metallographic image. Many researchers have applied some excellent digital image segmentation algorithms to the grain segmentation of metallographic image. As for the second research idea, it mainly focuses on the research of grain boundary extraction in metallographic images, and the most common method is to apply the edge extraction algorithm to grain boundary extraction in metallographic images. Many researchers continue to try on the basis of the existing algorithm, broaden their thinking, and achieve certain results by combining other algorithms.

However, according to the changes of the data set, the processing methods of these two roads vary greatly, and it is difficult to accurately segment the more complex metallographic images. In recent years, with the rapid development of computer vision, deep learning is widely used in cell segmentation, road scene segmentation, etc., and achieved excellent results, so we apply deep learning to metallographic image segmentation.

Since 2012, deep learning methods [17] have dominated many computer vision applications. This includes object recognition and detection, scene fusion, semantic segmentation and depth map prediction. The success of deep learning is often attributed to the fact that convolutional neural network (CNN) can effectively represent the visual data hierarchy, and combine the low-level image features (edges, color gradients) into the higher-level features (such as object parts) corresponding to the abstract quality of the image theme. Recently materials scientists have begun to explore the limited applications of modern computer vision techniques for flexible and universal microstructure characterization. Ref [18] and [19] explored these techniques in the context of microstructure classification. Ref [20] and [21] used the pre-trained CNN representation to study the relationship between the processing conditions and the microstructure obtained through the descending and visualization techniques. Ref [22] CNN segmentation model was used to identify the constituent phase of steel structure.

In recent years, various depth CNN architectures have been developed for intensive pixel-level tasks [23], such as semantic segmentation [24], edge detection, depth map, surface normal prediction [25], etc. Conceptually, it is the modern deep CNN that computes a highly nonlinear function by layer-by-layer combination of convolution, activation, and pooling (i.e., down-sampling) functions whose parameters are obtained from large annotated data sets through some variants of stochastic gradient descent [25,26].The classification neural network simplifies the input image into a single potential feature vector, in which the neural network designed for the pixel level task generates a potential representation for each pixel of the input image. This is usually achieved by fixed bilinear interpolation [26] or learning deconvolution operations [27]. In the latter network, the popular architectures are SegNet [24], Bayesian SegNet [28], u-net [29] with large data increment, and fully convoluted DenseNets [23]. In particular, u-net [29] is designed for medical image segmentation tasks with small data sets, and it relies on powerful data expansion to achieve good performance.

In this work, we apply the deep learning method to the image segmentation for complex microstructure data, aiming to extend the scope of quantitative analysis to metallographic microstructure systems.

**目前，已经有许多研究人员对晶界提取进行了大量的理论探索与实验研究，并且取得了显著的进步。现阶段，主流的研究思路主要分为两个方向[12]：一是对金相图像中的晶粒进行分割，目的是得到一块块完整的晶粒，晶粒与晶粒之间的邻接处便是晶界，主要使用的方法是：分水岭分割算法[13]、水平集分割算法[14]、聚类分割算法等等；二是利用一些算子对金相图像中的晶界直接进行提取，典型的有：canny 算子[15]、Sobel 算子[16]、kirsch算子等等。对于第一条研究思路，主要研究重心是金相图像中的晶粒，许多研究人员已经将一些优秀的数字图像分割算法应用到金相图像晶粒分割当中。对于第二条研究思路，主要着重于金相图像中晶界提取的研究，最常见的就将边缘提取算法应用到金相图像晶界提取当中。许多研究人员在已有算法基础上不断尝试，开拓思路，通过结合其他算法取得了一定的效果。**

**但这两条路，根据数据集的变化，处理方式会有很大变化，而且对于较为复杂的金相图像很难准确分割。近些年来，随着计算机视觉的飞速发展，深度学习广泛用于细胞分割，道路场景分割等，且取得了极好的效果，故将深度学习与金相显微结构结合起来。**

**自从2012年以来，深度学习方法【17】已经主导了许多计算机视觉应用。包括目标识别与检测，场景融合，语义分割和深度地图预测。深度学的成功往往归功于卷积神经网络（CNN）能够有效的表示视觉数据层次结构，将低层次的图像特征（边缘，颜色梯度）组合成对应于图像主题抽象品质的更高层次的特征（如对象部分）。最近材料科学家已经开始探索现代计算机视觉技术在柔性和通用显微结构表征方面的有限应用。[8]和[9]在微观结构分类的背景下探索这些技术。[10]和[11]使用预先训练的CNN表示来研究处理条件之间的关系，以及通过降维和可视化技术获得的微观结构。[12]使用CNN分割模型来识别钢组织的组成相。近年来，针对密集像素级任务[16]开发了各种深度CNN架构，如语义分割[17]、边缘检测、深度地图、表面法线预测[18]等。从概念上讲，是现代的深度CNN通过卷积、激活和池化(即下采样)函数的逐层组合来计算一个高度非线性的函数，这些函数的参数是通过随机梯度下降的某些变体从大型带注释的数据集中获得的[18,19]。分类神经网络将输入图像简化为单个潜在特征向量，其中针对像素级任务设计的神经网络为输入图像的每个像素生成潜在表示。这通常是通过固定双线性插值[13,19]或学习反褶积操作[20]来实现的。在后一类网络中，比较流行的架构有SegNet[17]、Bayesian SegNet[21]、数据增量大的U-Net[22]、全卷积DenseNets[23]。特别是U-Net[22]，它是为小数据集规模的医学图像分割任务而设计的，依靠强大的数据扩充来获得良好的性能。**

**目前非常新的有deeplabV3+等等。**

**在这项工作中，我们将深度学习方法应用于复杂的微观结构数据的图像分割，目的是将定量分析的范围扩展到金相微观结构系统。**