Title:
A Novel Approach to Metallographic Grain Size Measurement Using Deep Learning and Computational Geometry Techniques

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Introduction:

Metallography is the analysis of microscopic images of materials to characterize their internal features, such as grains, phases, and inclusions. It is essential in materials science because these microstructural characteristics strongly influence properties such as strength, toughness, and corrosion resistance. Accurate metallographic analysis plays a critical role in optimizing the performance and reliability of metal materials, especially in safety-critical and high-performance applications across industries such as automotive manufacturing, aerospace, small arms safety, and structural engineering. Among various metallographic assessments, grain size measurement is particularly important, since the average grain size often governs key performance attributes of the material [1]. Despite its significance, grain size measurement remains predominantly manual, making it time-consuming and susceptible to human bias.

Given these challenges, numerous automated methods have been proposed that use either classical image processing or deep learning for boundary detection. Each approach, however, faces challenges. Rule-based algorithms work well when grain boundaries are sharply defined but can fail in the presence of complex microstructures [2]. Deep learning methods, while more adaptable, may introduce recognition errors or overlook certain boundaries if the training data or tuning parameters are suboptimal [3]. Such inaccuracies eventually degrade the reliability of the measured grain size.

To address these shortcomings, we propose a novel approach that combines deep learning-based segmentation with specially designed post-processing steps using computational geometry concepts. In particular, our method incorporates advanced topological skeleton analysis to enhance the overall quality of the grain boundary representations. This integration improves the continuity and clarity of the boundaries by mitigating noise and discontinuities typically associated with the segmentation process. Validated on real-world metallographic datasets, our approach is efficient, scalable, and demonstrates robust performance across diverse microstructures and preparation conditions. This performance bridges traditional metallography with computer-aided design (CAD) techniques, enabling automatic and reliable grain size measurement, and advancing metallographic analysis.

Main Idea:

Our proposed approach for automatic grain size measurement comprises three key steps: grain boundary extraction, grain boundary cleaning, and grain size computation using the intercept method. Fig. 1 illustrates the overall structure of our approach and outlines the key steps involved in the process.

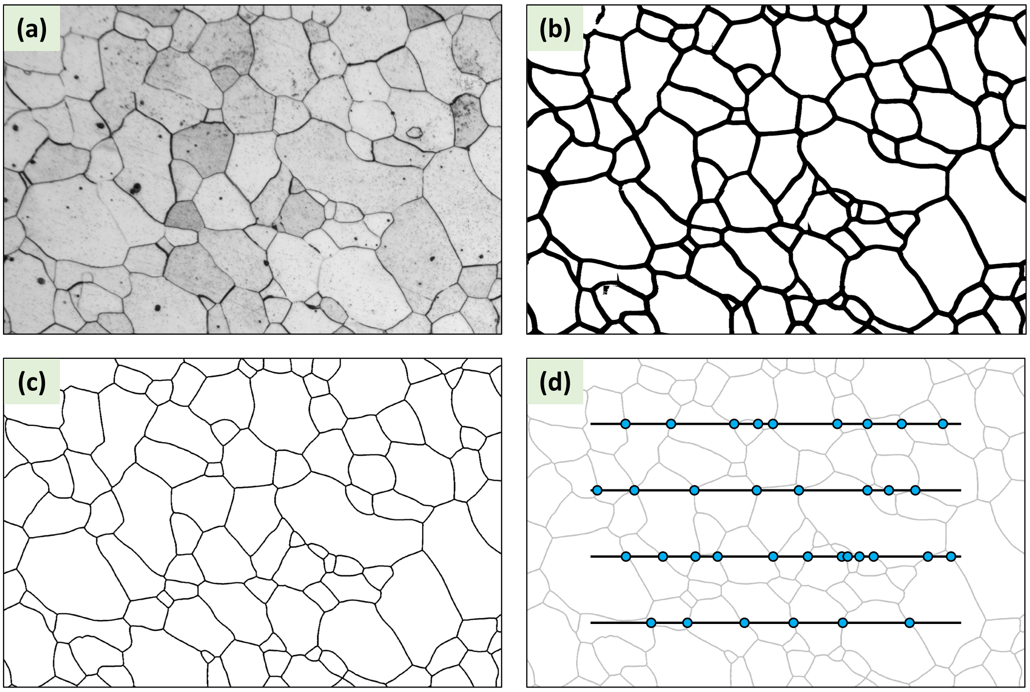

Fig. 1: Overview of the proposed approach for automatic grain size measurement. (a) Input metallographic image, (b) grain boundary extraction using the U-Net model, (c) grain boundary cleaning using a topological skeleton-based process, and (d) final grain size calculation via the intercept method.

1. Grain Boundary Extraction: In the initial step, we train and deploy a U-Net model to segment grain areas and grain boundary regions from input metallographic images. While U-Net effectively identifies the majority of grain boundaries, it may also detect some grain boundary artifacts and feature imperfections due to segmentation inaccuracies and the inherent complexities of material structures.

2. Grain Boundary Cleaning: The second step involves refining the extracted grain boundaries through a topological skeleton-based cleaning process. Utilizing computational geometry concepts, we analyze the main boundary topologies and iteratively remove minor, dangling branches while retaining larger or more complete branches that correspond to genuine grain boundaries. This process minimizes the impact of artifacts and imperfections, ensuring a more accurate representation of the grain structure.

3. Grain Size Computation: Finally, we apply the intercept method, a standardized technique for grain size measurement, to quantify grain sizes based on the cleaned grain boundaries. The intercept method involves overlaying test patterns on the metallographic images and calculating grain size by counting the intersections of these patterns with the grain boundaries. Our approach mitigates the intercept method's sensitivity to small noisy areas and its insensitivity to broken grain boundary ends by integrating the previous steps, thereby enhancing the overall accuracy and reliability of grain size measurements.

Grain Boundary Extraction:

We utilize the U-Net architecture [4] to segment grain boundaries from metallographic images. U-Net is a well-established model for semantic segmentation and is suitable for high-resolution microscopy data, enabling a clear distinction between grain boundary regions and grain areas.

A dataset of 400 real-world metallographic images was collected and labeled, encompassing materials such as high-purity iron and stainless steels produced and imaged under diverse conditions. Each image was systematically partitioned into 512×512 patches with a stride of 128, a process that both expands the dataset and mitigates computational demands during training. These patches were then split into training (60%), validation (20%), and testing (20%) sets. Additionally, the same testing subset was manually annotated for grain size measurement using the intercept method, thus enabling an overall evaluation of our complete approach.

To mitigate the risk of overfitting, several regularization strategies were integrated into our training process. Specifically, dropout layers with a rate of 0.3 were inserted after each convolutional block in the encoder path of the U-Net architecture, and L2 weight regularization with a coefficient of 1×10^{-4} was applied to the network parameters. Furthermore, data augmentation was performed using horizontal flipping, vertical flipping, 90° rotations in both clockwise and counterclockwise directions, and contrast enhancement. We also conducted 10-fold cross validation on the training set to ensure robust hyperparameter tuning and reliable performance evaluation.

Although U-Net successfully identifies the majority of grain boundaries, certain challenges remain. Noise introduced during metallographic preparation and incomplete etching can cause some impurities to be misclassified as boundaries, while partially corroded boundaries may be misclassified as grains. Consequently, actual boundaries may appear as dangling branches that are not fully connected, and other noise-like features may be erroneously labeled as valid boundaries. These artifacts can undermine the accuracy of subsequent grain size measurements. Therefore, in the next step, we refine and correct the initially segmented boundaries to address these limitations.

Grain Boundary Cleaning:

After the U-Net segmentation, we refine the identified grain boundaries by extracting their topological skeleton and removing incorrect segments. The skeleton representation simplifies the topology of grain boundaries, making it easier to distinguish genuine boundaries from undesired artifacts such as segmentation noise and falsely detected structures within the microstructure. This property allows for a systematic refinement process, ensuring that spurious branches and noise can be effectively identified and removed while preserving true grain boundaries.

First, we apply a morphological opening operation to eliminate isolated image noise and smooth any jagged edges from the U-Net output. Next, we compute the skeleton of the segmented grain boundaries, which enhances the structural clarity of the extracted boundaries. To remove short, dangling branches, we set a threshold at 50% of the average branch length. Fully connected boundaries remain unaffected by this threshold to ensure the preservation of genuine boundaries. Since pruning can introduce new dangling ends, we iteratively update the skeleton, recalculate the average branch length, and remove newly formed short branches until no further dangling branches remain.

The skeleton-based cleaning process is summarized in Algorithm 1.

Grain Size Computation:

Following grain boundary extraction and cleaning, the resulting skeleton captures continuous boundaries and retains any long, dangling branches that correspond to actual grain edges. This step is critical for the intercept method prescribed by ASTM E112 [5], which is relatively insensitive to small breaks in boundaries but highly sensitive to noise and artifacts. By removing short, spurious branches and preserving longer, valid edges, our approach ensures that subsequent grain size measurements accurately

Algorithm 1 Skeleton-Based Grain Boundary Cleaning

procedure SKELETONCLEANING(I_{seg})
    $I_{\text{open}} \leftarrow$ MORPHOLOGICALOPENING(I_{seg})
    $S \leftarrow$ SKELETON(I_{open})
    $L_{\text{avg}} \leftarrow$ AVERAGEBRANCHLENGTH(S)
    $T \leftarrow 0.5 \times L_{\text{avg}}$ ▷ Threshold set to 50% of average branch length
    pruningOccurred $\leftarrow$ **true**
    while pruningOccurred **do**
        pruningOccurred $\leftarrow$ **false**
        for each branch $b \in S$ **do**
            if ISDANGLING(b) **and** LENGTH(b) $< T$ **then**
                $S \leftarrow$ REMOVEBRANCH(S, b)
                pruningOccurred $\leftarrow$ **true**
            end if
        end for
        if pruningOccurred **then**
            $L_{\text{avg}} \leftarrow$ AVERAGEBRANCHLENGTH(S)
            $T \leftarrow 0.5 \times L_{\text{avg}}$
        end if
    end while
    return S
end procedure

reflect the true microstructure.

The intercept method draws test patterns (e.g., lines or circles) over the metallographic image and counts the intersections between these patterns and the identified grain boundaries. From these counts, the official ASTM grain size number G is computed using the following formula [5]:

$$G = -3.288 \; - \; 6.643856 \times \log_{10}\!\left(\frac{L}{M \times N}\right), \tag{2.1}$$

where L is the total length of the test patterns in millimeters, M is the magnification factor of the microscope, and N is the number of intersections counted. By aligning with a widely recognized standard, this method enables our final grain size measurements to be directly compared across different laboratories and material systems.

<u>Results:</u>

We first evaluated the U-Net segmentation performance on a test dataset of 80 real-world metallographic images (as mentioned in the "Grain Boundary Extraction" section) at a resolution of 5472×3648, achieving a pixel-level accuracy of 95.4% and a mean Intersection over Union (mIoU) of 86.5%. Although most grain boundaries were accurately identified, some artifacts and incomplete boundaries persisted, underscoring the necessity for the subsequent skeleton-based cleaning step.

Next, we invited professional metallurgists to manually measure the grain size numbers on these images using the intercept method, providing ground truth for comparison. Table 1 compares our (U-Net + skeleton + intercept) method with several other automatic approaches that are either widely used or considered likely to yield good results, all employing the same intercept test patterns.

By integrating deep learning and computational geometry, our method achieves the lowest mean absolute error (0.034) in grain size number among the tested approaches and processes each image in

Table 1: Comparison of different grain size measurement approaches.

Approach	Mean Absolute Error	Implementation Time (s)
Manual (Ground Truth)	0	99.17
U-Net + Intercept	0.219	2.81
U-Net + Skeleton + Planimetric	0.148	4.90
U-Net + Skeleton + Intercept (Ours)	0.034	5.04

about 5 seconds, compared to approximately 99 seconds for manual measurement. This outcome confirms that our integrated workflow not only significantly reduces the time and effort required for manual analysis but also outperforms other automatic methods in accuracy, demonstrating its robustness and effectiveness in real-world metallographic analysis.

Conclusions:

In this paper, we presented a novel approach for metallographic grain size measurement that integrates deep learning and computational geometry techniques. By employing the U-Net model for initial segmentation and a skeleton-based cleaning procedure to refine grain boundaries, our method effectively addresses common issues such as noise, incomplete etching, and branching artifacts. The subsequent application of the intercept method, which follows the ASTM E112 standard, ensures that the final grain size measurements are both accurate and comparable across different laboratories.

Experimental evaluations on real-world metallographic datasets show that our approach achieves state-of-the-art accuracy among automatic grain size measurement methods, with a mean absolute error of 0.034 in grain size number. Additionally, it significantly improves efficiency by reducing the processing time to approximately 5 s per image, compared to 99 s for manual measurement. By retaining critical boundary information and eliminating noise, our integrated system provides a reliable, fast, and easily adaptable solution for a range of material systems and imaging conditions, making it a valuable tool for advancing metallographic analysis in both research and industrial settings.

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References:

[1] Sarkar, A.; Prasad, M.; Murty, S.: Effect of initial grain size on hot deformation behaviour of Cu-Cr-Zr-Ti alloy, Materials Characterization, 160, 2020, 110112. https://doi.org/10.1016/j.matchar.2019.110112

[2] Li, X.; Cui, L.; Li, J.; et al.: Automation of intercept method for grain size measurement: A topological skeleton approach, Materials & Design, 224, 2022, 111358. https://doi.org/10.1016/j.matdes.2022.111358

[3] Rathod, K.; Choudhary, A. K.; Jansche, A.; et al.: GeGra: Approaching a generic model for quanti-

tative grain size analysis from materials microscopy data using deep learning, Materials Characterization, 217, 2024, 114379. https://doi.org/10.1016/j.matchar.2024.114379

[4] Ronneberger, O.; Fischer, P.; Brox, T.: U-net: Convolutional networks for biomedical image segmentation, MICCAI 2015, 2015, 234-241. https://doi.org/10.1007/978-3-319-24574-4_28

[5] ASTM International: ASTM E112-13(2021) Standard test methods for determining average grain size, Standard, ASTM International, 2021. https://www.astm.org/e0112-13r21.html

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