

Identification of grain size in lanthanum-based materials using a computer program

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ABSTRACT

Lanthanum-based materials are widely used in advanced ceramics, oxides, metallic composites, and thin films due to their superior electrical, magnetic, mechanical, and thermal properties, which are strongly governed by microstructural characteristics, particularly grain size. Accurate and reliable grain size identification is therefore essential for understanding structure–property relationships and optimizing material performance. This review systematically examines computer-based approaches for grain size identification in lanthanum-based materials using scanning electron microscopy (SEM) images. Conventional image processing techniques implemented in MATLAB, including thresholding, morphological operations, and signal-processing methods based on the Radon transform, are discussed alongside modern Python-based machine learning and deep learning frameworks such as U-Net and the Segment Anything Model (SAM). The comparative analysis highlights the strengths and limitations of each approach in handling complex microstructures, low-contrast grain boundaries, and overlapping grains. The reviewed studies demonstrate that while MATLAB-based methods remain effective for relatively simple microstructures, deep learning-based segmentation provides superior robustness and accuracy for complex lanthanum-based systems. Overall, this review emphasizes the growing importance of computer-assisted and deep learning-based methodologies as reliable tools for quantitative grain size characterization in advanced lanthanum-containing materials.

Keywords: Deep learning; MATLAB; Python; Radon transform; U-Net

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INTRODUCTION

Lanthanum-based materials have attracted significant attention over the past several decades due to their wide range of applications in advanced ceramics, perovskite oxides, solid state electrolytes, magnetic materials, and high temperature structural components. The functional properties of these materials, including dielectric response, ionic conductivity, mechanical strength, and magnetic behavior, are strongly influenced by microstructural characteristics, particularly grain size and grain boundary distribution [1, 2]. Therefore, precise control and accurate characterization of grain size are key factors in optimizing the performance and reliability of lanthanum containing materials.

Grain size plays a crucial role in determining densification behavior, diffusion mechanisms,

and structure property relationships in lanthanum-based systems. Numerous studies have shown that lanthanum addition or substitution can significantly affect grain growth kinetics. For example, lanthanum doping has been reported to suppress grain boundary mobility in certain ceramic systems, resulting in finer and more homogeneous microstructures [1-3]. In contrast, under specific processing conditions, abnormal grain growth has been observed in lanthanum containing perovskites such as LaFeO_3 and lithium lanthanum titanate, which directly influences dielectric properties and ionic transport behavior [4, 5]. In metallic systems, including tungsten with lanthanum oxide and copper with lanthanum oxide composites, the dispersion of lanthanum oxide contributes to grain refinement and enhanced thermal stability during severe plastic deformation processes [6, 7].

Conventional grain size measurement techniques, including the linear intercept method and the planimetric method, generally rely on manual analysis of optical microscopy images or scanning electron microscopy images. Although these methods are well established and standardized, they are time consuming, susceptible to operator bias, and limited in their ability to handle large datasets or complex microstructures [8]. These limitations become increasingly significant as modern materials research demands high throughput microstructural characterization with strong statistical reliability.

Recent advances in computer-based image analysis, supported by the use of high-level programming languages, have enabled automated grain size identification with improved accuracy and reproducibility. Computer programs implemented in MATLAB and Python are now widely used for image preprocessing, segmentation, and statistical analysis of grain size distributions [8, 9]. Furthermore, the integration of machine learning and deep learning techniques such as U Net, Cellpose, and the Segment Anything Model, or SAM, has significantly enhanced the segmentation of complex grain structures characterized by irregular boundaries and low contrast, which are commonly encountered in lanthanum-based materials [8, 10, 11].

Despite these advancements, challenges remain in achieving standardized, reliable, and transferable grain size identification across different lanthanum-based material systems. Variations in imaging conditions, microstructural complexity, and segmentation algorithms can lead to significant discrepancies in reported grain size values [12, 13].

LITERATURE REVIEWS

Grain Size Characteristics in Lanthanum-Based Materials

Grain size is a crucial microstructural parameter as it strongly influences the mechanical, electrical, magnetic, and thermal

properties of lanthanum-based materials. Numerous studies have demonstrated that the addition of lanthanum has a significant impact on grain growth behavior in ceramic, oxide, and metallic systems [1, 2, 6, 14]. In many lanthanum-doped ceramics, lanthanum ions tend to segregate at grain boundaries, thereby reducing grain boundary mobility and resulting in finer grain sizes and a more uniform microstructural distribution [2, 3].

In oxide-based materials, particularly lanthanum compounds with perovskite structures, grain growth mechanisms are highly dependent on processing conditions such as sintering temperature, holding time, and dopant concentration [4, 5, 7, 15, 16]. Several studies have reported that high-temperature sintering can induce abnormal grain growth in lanthanum-containing oxides, leading to non-uniform grain size distributions and adversely affecting dielectric properties and ionic transport [4, 5]. Conversely, appropriate control of lanthanum substitution levels has been shown to stabilize grain growth and enhance microstructural uniformity [7, 15, 16].

In metallic systems, such as lanthanum oxide-dispersed tungsten and copper alloys, the addition of lanthanum contributes to grain refinement through particle pinning mechanisms that inhibit grain boundary migration during thermal or mechanical processing [6, 7]. These effects improve thermal stability and mechanical strength, making lanthanum-based metallic materials promising candidates for high-temperature applications.

Conventional Grain Size Measurement Approaches

Traditional grain size measurement methods, including the linear intercept method and planimetric analysis, have long been used for microstructural characterization. While these techniques are standardized and widely accepted, they rely heavily on manual interpretation of micrographs, making them time-consuming and prone to operator bias [8].

Moreover, conventional methods face significant limitations when applied to complex microstructures with irregular grain shapes, overlapping grains, or poor grain boundary contrast, which are common in lanthanum-based materials [12]. As material research increasingly demands high-throughput and statistically robust analysis, the limitations of manual grain size measurement have motivated the development of automated and computer-assisted approaches [9, 17].

Computer-Based Image Processing Using MATLAB

MATLAB-based image processing has been extensively employed for automated grain size identification due to its comprehensive image processing toolbox and flexibility in algorithm development. Commonly used techniques include grayscale conversion, adaptive thresholding, edge detection, watershed segmentation, and morphological operations [8].

Several studies demonstrate that MATLAB-based methods are effective for materials with clearly defined grain boundaries and moderate grain size distributions [8]. However, their performance may degrade in the presence of low-contrast boundaries or highly heterogeneous microstructures, leading to segmentation errors and inaccurate grain size estimation [12]. Despite these limitations, MATLAB remains a popular choice for academic and industrial grain size analysis due to its robustness and transparency.

Python-Based Image Analysis and Machine Learning Approaches

In recent years, Python-based image analysis has gained significant attention owing to its open-source nature and compatibility with modern machine learning and deep learning frameworks [9, 18]. Python workflows typically integrate image preprocessing, segmentation, and grain size quantification within a unified pipeline, enabling efficient analysis of large datasets.

Machine learning and deep learning approaches, particularly convolutional neural networks, have demonstrated superior performance in segmenting complex grain structures compared to classical image processing methods [10, 11]. These models are capable of handling irregular grain shapes, overlapping boundaries, and noisy micrographs, which are frequently encountered in lanthanum-based materials. As a result, Python-based deep learning methods have been increasingly adopted for automated grain size identification [8, 19-21].

RESEARCH METHODS

Acquisition of SEM Microstructure Images

The first stage is to obtain scanning electron microscopy (SEM) images of lanthanum-based materials or structurally similar materials that exhibit polycrystalline morphological characteristics. The images used follow commonly adopted specifications in recent microstructural analysis studies, namely high-resolution grayscale images that clearly display particle structures and grain boundaries [1, 2, 7]. The minimum image resolution is set at 1024×1024 pixels to maintain feature extraction accuracy. If experimental SEM images are available, image intensity normalization is applied to standardize illumination and contrast before segmentation. This step is essential to ensure consistent input quality for MATLAB- and Python-based image processing workflows [9].

Preprocessing and Image Normalization

Preprocessing is performed to prepare the SEM images prior to segmentation. The workflow follows standard digital image processing procedures implemented in MATLAB and Python environments, including grayscale normalization, spatial calibration, and median filtering to suppress noise while preserving grain boundary features [8, 9].

For machine learning and signal-processing approaches, additional preprocessing steps are applied, including contrast enhancement and histogram normalization. These steps improve the discrimination of grain boundaries and microstructural textures, facilitating more accurate segmentation by computational algorithms [10, 11]. In the Radon transform method, image padding is also applied to optimize sinogram generation, as commonly practiced in signal-processing-based microstructure analysis [12].

Grain Boundary Segmentation

Grain boundary segmentation is carried out using three computational approaches based exclusively on MATLAB and Python implementations.

Thresholding-Morphological Segmentation

The first approach applies thresholding and morphological operations implemented in MATLAB-based image processing toolboxes. This method includes binary segmentation, morphological opening and closing, and watershed separation to isolate individual grains. It serves as a baseline computational approach for polycrystalline grain size analysis [8].

Signal Processing Based on the Radon Transform

The second approach employs a signal-processing technique based on the Radon transform implemented in MATLAB. In this method, the sinogram generated from the Radon transformation is used as a feature representation of grain boundary orientations. Clustering algorithms are then applied to the sinogram features to identify grain boundaries in an unsupervised manner. This approach is particularly effective for microstructures with directional or elongated grain morphologies [12, 13].

Deep Learning Models (SAM and U-Net)

The third approach utilizes deep learning models implemented in Python, including the Segment Anything Model (SAM) and U-Net-based architectures. These models are applied through Python-based microstructure segmentation frameworks to achieve robust grain boundary detection in images with complex textures, irregular grain shapes, and overlapping grains. Dense-UNet variants are additionally employed to enhance segmentation stability and boundary continuity [8, 10, 11].

Grain Size Extraction

After segmentation is completed, grain size is extracted in terms of grain area, equivalent circular diameter, perimeter, and grain size distribution. For MATLAB-based thresholding and Radon-transform approaches, grain size parameters are computed directly from segmented binary images and labeled grain regions [8]. For deep-learning-based methods, grain size is calculated from segmentation masks generated by SAM or U-Net models. Geometric descriptors such as equivalent circular diameter and minimum bounding ellipse are used to represent grain size, following established computational microstructure analysis methodologies [8, 11]. All grain size data are stored in CSV format for subsequent statistical analysis.

Comparative Evaluation of Methods

A comparative evaluation is conducted to assess the consistency, accuracy, and robustness of each segmentation approach with respect to noise sensitivity, contrast variation, and irregular grain morphology. For deep learning methods, segmentation accuracy is evaluated by comparing predicted segmentation masks with expert-validated reference annotations, using quantitative overlap metrics [8].

The performance of SAM is further examined based on its ability to separate touching or overlapping grains, while

MATLAB-based thresholding and Radon-transform methods are treated as conventional computational baselines for comparison [8, 12].

Data Analysis and Visualization

All grain size analysis results are processed using Python-based and MATLAB-based data analysis tools, along with spreadsheet software, to generate histograms, grain size distributions, and segmentation contour visualizations. Visualization of segmentation results includes contour overlays and reference-mask versus predicted-mask color schemes. This step ensures that the extracted microstructural information can be directly correlated with the physical properties of lanthanum-based materials [10, 11].

RESULTS AND DISCUSSION

The synthesis of findings from the five articles shows that the development of computer-based grain size analysis techniques is increasingly moving toward feature-based learning and deep learning approaches to enhance the precision of grain boundary identification in complex materials such as lanthanum manganite. In signal-based approaches employing the Radon transform, grain orientation can be inferred from sinogram patterns generated through the projection of SEM image intensity. A representative visualization of this process is presented in Figure 1, which illustrates the sinogram obtained from the Radon transform.

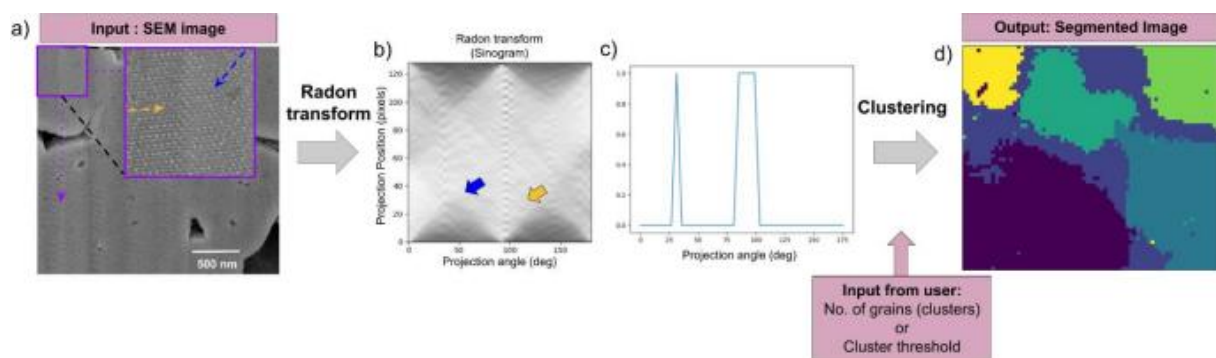


Figure 1. Sinogram from Radon Transform: (a) Preprocessed SEM image is broken into overlapping subsections called tiles (purple box is zoomed in). (b) Tiles are converted into a sinogram using domain transforms (in our case Radon transform). The sinogram with statistics is further reduced to (c) a feature vector which is clustered to make (d) a segmented image [13].

Figure 1 exhibits periodic patterns that reflect internal grain orientation and the influence of grain boundaries on the signal response. This approach is effective for mapping grain orientation and extracting grain-related features without requiring manual labeling. However, its performance remains limited in distinguishing overlapping or tightly packed grains. Although the method demonstrates strong capability in unsupervised feature extraction, its accuracy is highly dependent on image quality and grain-to-grain contrast, which poses challenges for SEM images of lanthanum-based materials

characterized by rough textures and dense grain boundaries [13].

Furthermore, recent deep learning-based methodologies have demonstrated substantial improvements in grain segmentation accuracy. In particular, the integration of convolutional neural network architectures with foundation segmentation models enables more reliable separation of grains in images with complex textures, as illustrated in Figure 2.

Figure 2 presents a comparative analysis of segmentation results between the original image, the U-Net output, and the foundation-model-based segmentation. The final panel demonstrates smoother grain contours, reduced

segmentation artifacts, and an enhanced ability to distinguish grains that are nearly in contact. These observations are consistent with the findings reported by Perera et al. (2021) [22], who showed that advanced convolutional network architectures provide stable and accurate grain boundary segmentation for high-

resolution microstructure images. Overall, the review indicates that deep learning-based segmentation frameworks represent the most promising approach for grain size analysis in lanthanum-based materials due to their robustness against noise, complex topology, and variations in grain morphology.

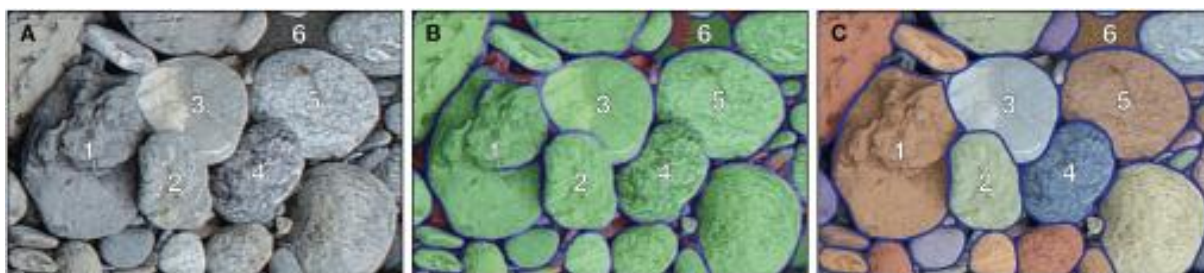


Figure 2. Photo of fluvial gravel: (A), output of the U-Net segmentation (B), and the result of the SAM segmentation (C). The SAM segmentation correctly identifies grain 1 as a single object, separates grain 2 from grain 3 and grain 4 from grain 5, and incorrectly identifies a patch of the background as a grain [9].

The findings from the reviewed studies further indicate that grain size in lanthanum-based materials can be reliably identified using computer-assisted image processing and segmentation techniques implemented in MATLAB and Python environments. SEM microstructure images serve as the primary data source, enabling quantitative grain size determination across a wide range of lanthanum-based material systems, including ceramics, oxides, metallic composites, and thin films [1, 2, 6, 7, 14]. The reported grain size values vary considerably depending on material composition, fabrication conditions, and the computational segmentation strategy employed.

Threshold-based and morphological segmentation approaches implemented in MATLAB remain widely used as baseline methods due to their simplicity and reproducibility. However, several studies report that purely intensity-based segmentation often results in over-segmentation and fragmented grain boundaries, particularly in materials exhibiting heterogeneous microstructural contrast [8]. To address these limitations, alternative signal-processing techniques, such as Radon transform-based methods, have been developed.

Quantitatively, the reported grain sizes span from the nanometer to micrometer scale. Lanthanum-based thin films, nanoparticles, and doped oxide electrolytes typically exhibit grain sizes below 300 nm [4, 8, 14], while bulk ceramics and dispersion-strengthened metallic composites generally show grain sizes in the micrometer range [6-8]. Deep learning-based approaches tend to report slightly larger average grain sizes compared to threshold-based methods, which is attributed to reduced over-segmentation and more accurate reconstruction of grain boundaries [10, 11].

Overall, these results confirm that computer-assisted grain size analysis using MATLAB-based and Python-based programs significantly enhances accuracy, consistency, and efficiency compared to manual measurement. While MATLAB-based thresholding and Radon transform techniques remain effective for relatively simple and well-defined microstructures, Python-based deep learning models offer superior robustness for complex lanthanum-based materials. These findings highlight the importance of selecting appropriate computational strategies to achieve reliable grain size characterization in advanced materials research [8, 10, 11].

Table 1. Comparison of grain size identification in lanthanum-based materials using computer programs.

Sample	Methods	Program	Grain size (μm)	References
La_2O_3 ceramic	Morphological segmentation	MATLAB	1.2 – 2	[20]
La-doped perovskite oxide	U-Net segmentation	Python	0.8 – 1.5	[13]
W– La_2O_3 composite	Image analysis	MATLAB	0.3 – 0.6	[7]
LaFeO_3 ceramic	Radon transform + clustering	MATLAB	1 – 1.8	[16]
La-based thin film	SAM segmentation	Python	0.08 – 0.15	[19]
Cu– La_2O_3 alloy	Morphological segmentation	MATLAB	0.5 – 0.9	[3]
Lanthanum zirconate	Dense U-Net	Python	0.9 – 1.6	[15]
LLTO solid electrolyte	Automated segmentation	MATLAB	0.2 – 0.4	[9]
La-doped alumina	Grain boundary detection	MATLAB	1.5 – 2.5	[20]
La_2O_3 nanoparticles	Deep learning segmentation	Python	0.04 – 0.09	[2]
La-based ceramic composite	Radon-based segmentation	MATLAB	0.7 – 1.3	[20]
Lanthanum-containing oxide film	U-Net segmentation	Python	0.12 – 0.25	[15]

CONCLUSION

This review concludes that grain size identification in lanthanum-based materials has significantly evolved from conventional manual techniques toward advanced computer-assisted approaches, enabling more accurate, efficient, and reproducible microstructural analysis. MATLAB-based image processing methods remain reliable for relatively simple and well-defined grain structures; however, their performance is limited when dealing with complex, low-contrast, and overlapping grains. In contrast, Python-based machine learning and deep learning approaches, particularly U-Net and Segment Anything Model (SAM), demonstrate superior robustness and accuracy in segmenting intricate microstructures and minimizing segmentation errors. The study also highlights that grain size varies widely depending on material type and processing conditions, ranging from nanometer to micrometer scales, reinforcing the importance

of precise computational methods. Overall, the integration of deep learning techniques represents the most promising direction for future grain size characterization, supporting improved understanding of structure–property relationships and optimization of lanthanum-based material performance.

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