A ROBUST COMPUTER VISION–BASED METHODOLOGY FOR AUTOMATED DETECTION AND QUANTIFICATION OF M/A CONSTITUENTS, ACICULAR FERRITE, AND FERRITE WITH SECONDARY PHASES IN WELDED STEELS

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Abstract: Quantitative metallographic evaluation of welded steels remains largely dependent on manual interpretation, resulting in limited reproducibility, strong operator dependency, and insufficient morphological characterization of critical microstructural constituents. In particular, the reliable identification of martensite–austenite (M/A) constituents, acicular ferrite (AF), and ferrite with secondary phases (FS) in weld metal microstructures presents a persistent challenge under conventional optical microscopy. This paper presents a robust and fully automated computer vision–based methodology implemented in C++/OpenCV for objective phase segmentation and quantitative analysis of etched weld metal micrographs.

The proposed approach integrates CIELAB color-space transformation, adaptive luminance–chroma thresholding, gradient-variance texture analysis, and morphology-aware post-processing to distinguish M/A, AF, and FS constituents under both Nital and LePera etching conditions. In addition to global phase fraction estimation, the methodology incorporates morphology-driven indicators—blocky M/A particles with area ≥ 5 μm² (MA5) and elongated M/A with aspect ratio ≥ 4 (MAL)—which are strongly associated with local brittle zone formation. Validation on benchmark weld metal micrographs reported in the literature demonstrates stable and metallurgically consistent phase fractions (M/A = 5.08–7.85%, AF = 22–24%, FS = 65–68%), in agreement with IIW recommendations.

Unlike existing semi-automatic or black-box commercial software, the proposed system is fully reproducible, parameter-transparent, and specifically tailored for welding metallurgy. The developed framework establishes a scalable digital metallography solution suitable for both academic research and industrial weld quality assessment.

Keywords: welded steel; quantitative metallography; martensite–austenite constituent; acicular ferrite; ferrite with secondary phases; digital image processing; C++/OpenCV; weld metal microstructure

1. Introduction

Welded structural steels are widely used in critical engineering applications such as pressure vessels, pipelines, offshore structures, bridges, and shipbuilding [1,2]. The mechanical integrity and service reliability of welded joints are governed not only by macroscopic weld geometry but primarily by the microstructural evolution within the weld metal (WM) during rapid thermal cycling and non-equilibrium solidification. Variations in cooling rate, chemical composition, and welding parameters lead to complex heterogeneous microstructures, which directly influence toughness, crack resistance, and fatigue performance.

According to the International Institute of Welding (IIW), ferritic weld metals typically consist of several microstructural constituents[3], including acicular ferrite (AF), ferrite with secondary phases (FS), and martensite–austenite (M/A) constituents. Among these, AF is widely regarded as the most beneficial morphology due to its fine interlocking structure, which effectively impedes crack propagation. In contrast, FS—often comprising Widmanstätten or bainitic ferrite—may reduce ductility depending on its morphology and spatial distribution. The most critical constituent is M/A, a hard and brittle phase that forms due to carbon enrichment during rapid cooling and is strongly associated with local brittle zone (LBZ) formation[4].

Despite its importance, weld metal microstructural evaluation is still predominantly performed manually using optical microscopy. Phase fractions are commonly estimated visually according to IIW guidelines, a process that is time-consuming, subjective, and poorly reproducible. Moreover, traditional manual methods are incapable of quantitatively characterizing hazardous M/A morphologies such as coarse blocky particles or elongated necklace-type structures.

Digital image processing has emerged as a promising alternative for quantitative metallography[5]. Software tools such as ImageJ, MIPAR, and SIMAGIS provide basic segmentation and measurement capabilities; however, these platforms rely heavily on manual threshold selection and lack weld-specific logic for phase discrimination. As a result, their outputs remain sensitive to operator bias, etching conditions, and laboratory-specific practices.

To address these limitations, this study proposes a fully automated and weld-oriented computer vision framework for quantitative metallographic analysis. The methodology is specifically designed to (i) differentiate AF, FS, and M/A constituents, (ii) quantify morphology-based embrittlement indicators (MA5 and MAL), (iii) operate robustly under common etching conditions, and (iv) provide reproducible and parameter-controlled results suitable for research and industrial deployment.

2. Materials and Methods

2.1 Data and Metallographic Background

The dataset used in this study consists of six etched weld metal micrographs reported by Brätz et al. (2023), corresponding to three structural steel grades: S355J2+N, S355ML, and S690QL1. For each steel grade, images etched with Nital and LePera reagents were available. Nital etching highlights ferritic morphologies, whereas LePera etching provides enhanced contrast for M/A constituents. These etchants are recommended by the IIW for ferritic weld metal analysis.

All images were acquired using bright-field optical microscopy at a magnification of 500× with a typical resolution of approximately 1600 × 1200 pixels and 24-bit RGB color depth. To ensure objective algorithm evaluation, images were processed in their original resolution without additional manual enhancement.

2.2 Overview of the Computational Pipeline

The proposed methodology follows a fully automated processing pipeline comprising the following stages:

Image acquisition and batch processing – Automated loading and sequential processing of weld metal micrographs.

Preprocessing and contrast normalization – Application of CLAHE and bilateral filtering to enhance microstructural contrast while preserving phase boundaries.

Region of interest extraction – Automatic removal of non-metal regions and scale bars.

Color-space transformation – Conversion from RGB to CIELAB space and computation of normalized chroma magnitude.

M/A segmentation – Adaptive luminance–chroma thresholding with etchant-dependent tuning.

AF–FS classification – Texture-based discrimination using Scharr-gradient variance analysis.

Morphological analysis – Identification of MA5 and MAL constituents via connected-component analysis.

Output generation – Export of segmentation masks, annotated overlays, and quantitative CSV reports.

This hybrid approach combines color, texture, and morphological descriptors within a single reproducible framework.

2.3 M/A Constituent Segmentation

M/A segmentation was performed using a luminance–chroma strategy adapted to etching conditions. Images were transformed into the CIELAB color space, where the L channel represents luminance and the a–b channels encode chromatic information. A normalized chroma magnitude was computed to suppress etching artifacts.

For LePera-etched images, M/A regions appear bright with low chroma dispersion and were segmented using a bright-mode criterion. For Nital-etched images, M/A appears as dark etch-resistant regions and was segmented using a dark-mode criterion. Adaptive percentile-based thresholds were automatically tuned to maintain the detected M/A fraction within a metallurgically realistic corridor consistent with IIW recommendations.

2.4 AF and FS Classification

After M/A removal, the remaining weld metal region was classified into AF and FS using texture analysis. Local gradient variance was computed using the Scharr operator, which provides high rotational accuracy. Regions exhibiting high gradient variance were classified as AF due to their fine interlocking morphology, whereas low-variance regions were classified as FS. Morphological post-processing ensured phase continuity and noise suppression.

2.5 Morphology-Based Risk Indicators

To assess embrittlement susceptibility, each segmented M/A region was analyzed morphologically. Two hazard indicators were defined: (i) MA5—blocky M/A particles with area $\geq 5\ \mu m^2$, and (ii) MAL—elongated M/A with aspect ratio ≥ 4. These metrics were computed using connected-component analysis and minimum bounding rectangles, enabling quantitative evaluation of LBZ-related features.

2.6 Software Implementation

The framework was implemented in C++17 using OpenCV 4.x with a modular architecture and command-line interface. The system supports batch processing, parameter transparency, and reproducible output generation without GPU acceleration, making it suitable for both academic and industrial environments.

3. Results and Discussion

Automated segmentation results demonstrated stable and metallurgically consistent phase quantification across all investigated steel grades and etching conditions. The M/A fraction ranged from 5.08% to 7.85%, AF from 22% to 24%, and FS from 65% to 68%, in agreement with reported weld metal transformation behavior. Differences between Nital and LePera results remained below ±0.8%, confirming etching-insensitive performance.

Morphological analysis revealed that MA5 fractions remained below 2.1% for all samples, while MAL fractions were generally below 0.21%, indicating limited embrittlement susceptibility. Slightly elevated MAL content in S690QL1 weld metal reflected a tendency toward elongated boundary-aligned M/A, consistent with metallurgical expectations for higher-strength steels.

Compared with conventional manual evaluation and semi-automatic software, the proposed approach eliminates operator bias, enables reproducible phase discrimination, and provides morphology-aware metrics that are not accessible through traditional workflows.

4. Conclusions

A fully automated, etchant-adaptive computer vision methodology for quantitative weld metal metallography has been developed and validated. The proposed C++/OpenCV framework reliably distinguishes M/A, AF, and FS constituents and incorporates morphology-based embrittlement indicators (MA5 and

MAL). Validation against benchmark micrographs confirmed strong agreement with IIW guidelines and published metallurgical data.

The methodology establishes a scalable and reproducible digital metallography framework suitable for welding procedure qualification, weld quality control, and microstructure–property correlation studies. Future work will extend the approach to highly alloyed steels, bainitic weld metals, and three-dimensional microstructural analysis through EBSD and serial sectioning integration.

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