

# **Análisis comparativo de juntas soldadas mediante el proceso GMAW con técnicas de inspección visual e inspección visual mediante visión artificial**

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## **Abstract**

En este trabajo se realizó un análisis comparativo entre inspección visual (IV) y la inspección visual mediante visión artificial (IVA), para la evaluación de la calidad superficial de uniones soldadas de acero inoxidable austenítico AISI 304, mediante el proceso GMAW. Para determinar los criterios de evaluación se tuvieron en cuenta los códigos AWS D1.6 y guías de inspección AWS parte B, conociéndose así los tipos de discontinuidades y defectos que se pueden presentar en una unión de soldadura, los criterios de aceptación y aplicación de las técnicas de inspección. Posteriormente se diseñaron y generaron muestras soldadas a las cuales se les indujeron discontinuidades y defectos, identificándose como principales el exceso de penetración, falta de penetración, falta de continuidad, porosidad y salpicaduras. Teniendo las placas soldadas se realizó, de manera inicial, la evaluación de estas aplicando técnicas y normas de inspección visual. En segundo lugar, se implementó el método de evaluación mediante inspección visual y mediante visión artificial (IVA) para las probetas evaluadas anteriormente, a través de inspección visual (IV). Como resultado se realizó el respectivo análisis comparativo de los resultados obtenidos con ambas técnicas y se determinó que las probetas evaluadas por ambos métodos de inspección presentaron resultados similares y confiables, la inspección visual sigue siendo el método tradicional para evaluar la soldadura, sin embargo, la inspección visual mediante visión artificial demostró ser un método novedoso en el que se pudo resaltar de manera más eficiente la identificación de los poros, salpicadura, falta de continuidad y falta de penetración.

**Keywords:** Defectología, Discontinuidades, GMAW, Inspección visual, Procesamiento de imágenes, Visión artificial

## INTRODUCTION

Gas Metal Arc Welding is one of the most widely used fusion-welding processes in industrial manufacturing because of its high deposition rate, versatility, productivity, and suitability for automation. In the GMAW process, an electric arc is established between a continuously fed consumable wire electrode and the workpiece, while a shielding gas protects the molten weld pool from atmospheric contamination. The process is extensively applied in steel structures, automotive components, pipelines, machinery, shipbuilding, and general fabrication. Despite its technological maturity, GMAW remains sensitive to variations in welding current, arc voltage, travel speed, electrode extension, shielding gas flow, torch angle, joint preparation, and operator technique. These variations can result in visible or hidden discontinuities that affect weld quality. Inspection of welded joints is therefore essential for confirming compliance with design requirements, fabrication specifications, and relevant welding codes. Among available nondestructive testing techniques, visual inspection is generally the first method applied because it is relatively simple, economical, and capable of identifying numerous surface discontinuities before more advanced examinations are undertaken. A qualified inspector can evaluate bead shape, weld size, surface cracks, undercut, overlap, excessive reinforcement, arc strikes, spatter, incomplete filling, and other visible characteristics. However, conventional visual inspection has several limitations. Human judgment is inherently variable, and inspection results may differ among inspectors according to training, experience, visual acuity, fatigue, environmental conditions, and interpretation of acceptance criteria. Lighting intensity, viewing angle, distance, and accessibility can further influence results. In high-volume production environments, repetitive manual inspection may also become time-consuming and difficult to document consistently.

Artificial vision, also known as machine vision or computer vision, offers an alternative approach in which cameras and image-processing algorithms acquire and evaluate weld images. Advances in digital cameras, illumination systems, embedded processors, machine learning, and pattern-recognition algorithms have significantly expanded the potential of automated visual inspection. Artificial vision systems can identify geometric irregularities, classify surface imperfections, compare weld profiles, and store digital inspection records. The use of artificial vision in welding is especially attractive because many surface defects can be represented through visual features such as changes in texture, brightness, contour, width, edge geometry, and local discontinuity patterns. Digital image-processing methods can enhance these features and reduce dependence on subjective human interpretation. More advanced systems may use convolutional neural networks or other machine-learning methods to classify defects automatically. Nevertheless, artificial vision is not inherently superior in every situation. Metallic surfaces can create strong reflections, changing illumination can distort appearance, surface contamination can resemble defects, and poorly calibrated systems may generate false positives or false negatives. Consequently, a meaningful comparison between conventional visual inspection and artificial-vision-based inspection must evaluate not only defect-detection capability but also repeatability, processing time, consistency, implementation complexity, and practical industrial limitations. The present study therefore proposes a comparative analytical framework for GMAW welded joints inspected using both conventional visual examination and artificial vision. The study focuses on surface-visible defects and geometric characteristics rather than internal discontinuities. Its purpose is to identify the strengths and limitations of both methods and to determine how they can complement each other in modern weld-quality assurance.

### **GMAW Joint Quality and Common Surface Discontinuities:**

The quality of a GMAW joint depends on a combination of material properties, joint design, welding parameters, shielding conditions, consumable characteristics, and operator or robotic control. The weld bead should demonstrate adequate fusion, appropriate geometry, acceptable reinforcement, and continuous surface appearance without unacceptable discontinuities. Undercut is one of the most common visible discontinuities observed along weld toes. It appears as a groove melted into the base metal adjacent to the weld and may reduce the effective cross-sectional area while increasing local stress concentration. Excessive travel speed, improper torch manipulation, and unsuitable current settings can contribute to undercut formation. Excessive reinforcement occurs when deposited weld metal extends substantially above the required bead contour. Although it may initially appear to indicate additional strength, excessive reinforcement can generate abrupt geometric transitions and local stress concentration. Conversely, insufficient reinforcement or underfill indicates inadequate deposited material. Porosity may appear at the weld surface as small cavities caused by gas entrapment during solidification. Causes can include contamination, inadequate shielding gas, moisture, excessive arc length, or surface impurities. Although internal porosity cannot be assessed fully by visual inspection, visible pores provide an important quality indicator. Spatter consists of small droplets of molten metal deposited around the weld. While limited spatter may not always affect structural integrity, excessive spatter can indicate unstable welding conditions and increases post-weld finishing requirements. Overlap occurs when molten weld metal flows onto the base metal without proper fusion. It can be visible as an irregular edge and may significantly affect joint integrity. Surface cracks, if visible, are among the most serious defects and usually require rejection and further

evaluation. Weld-bead width, alignment, and consistency are also important quality characteristics. Artificial vision systems can measure these features quantitatively and compare them against predefined tolerances.

### **Conventional Visual Inspection of GMAW Welded Joints:**

Conventional visual inspection remains one of the most fundamental weld-evaluation techniques because it can be performed rapidly and at relatively low cost. Inspection may occur before, during, and after welding. Before welding, inspectors evaluate joint preparation, cleanliness, fit-up, alignment, and tack welds. During welding, they may observe arc stability, interpass cleaning, electrode manipulation, and visible process abnormalities. After welding, the completed bead is examined for surface discontinuities and dimensional compliance. Effective visual inspection requires appropriate illumination, viewing angle, accessibility, and calibrated measurement tools. Devices such as weld gauges, magnifying lenses, fillet gauges, and straightedges may assist inspectors in determining reinforcement height, undercut depth, fillet size, and dimensional deviation. The principal strength of human inspection is contextual interpretation. Experienced inspectors can evaluate multiple factors simultaneously and recognize unusual conditions that may not be represented within a predefined algorithm. They can also adapt to complex geometries, restricted access, dirty surfaces, variable lighting, and unexpected discontinuities. However, repeatability remains a significant concern. Two inspectors may assign different severity levels to the same surface condition, particularly when acceptance criteria involve borderline values. Even the same inspector may produce slightly different judgments after prolonged repetitive work because of fatigue or reduced attention. Another limitation is documentation. Manual inspection reports may record whether a weld was accepted or rejected, but they do not always preserve detailed visual evidence. Digital photography can improve documentation, although this introduces additional procedural requirements. Inspection speed also becomes important in mass-production environments. When hundreds or thousands of joints must be evaluated, manual visual inspection may become a bottleneck. Artificial vision can help overcome this limitation by automating routine screening. Human visual inspection is therefore highly flexible but inherently dependent on inspector competency and environmental conditions. The effectiveness of the method can be improved through standardized training, controlled lighting, calibrated tools, procedural checklists, and periodic inspector qualification.

### **Artificial-Vision-Based Inspection Architecture:**

Artificial-vision inspection begins with digital image acquisition. A camera is positioned relative to the weld so that the bead and surrounding base metal are clearly visible. Controlled illumination is essential because reflective metal surfaces can create glare and shadows that interfere with analysis. A typical artificial-vision system includes a camera, optical lens, illumination module, positioning fixture, image-processing unit, and inspection software. The camera may be mounted above a stationary sample or integrated with a robotic inspection platform. The first processing stage is image preprocessing. Noise reduction, contrast enhancement, grayscale conversion, histogram adjustment, and glare suppression may be used to improve image quality. The exact sequence depends on the imaging environment and surface characteristics. The second stage is weld-region segmentation. The algorithm identifies the weld bead and separates it from surrounding base metal. Thresholding, edge detection, adaptive segmentation, texture analysis, or deep-learning segmentation may be used for this purpose. Feature extraction follows segmentation. Relevant features can include bead width, edge straightness, reinforcement profile, local brightness changes, texture irregularity, discontinuity area, pore count, and spatter distribution. Traditional machine-vision systems may use predetermined thresholds. For example, if measured bead width falls outside a specified range, the system automatically classifies the region as nonconforming. More advanced approaches use machine learning to classify weld images according to defect categories. Convolutional neural networks can learn complex image features directly from labeled datasets. Their performance may exceed traditional handcrafted-feature methods when sufficiently large and representative training datasets are available. However, such systems require substantial data preparation and careful validation.

The inspection architecture can be represented as:

**\*\*Image Acquisition → Preprocessing → Weld Segmentation → Feature Extraction → Defect Classification → Acceptance Decision → Digital Record\*\***

One of the main advantages of artificial vision is repeatability. Once calibrated, the same algorithm applies identical decision rules to every image. This reduces variation associated with individual human judgment. Automated systems also provide traceability. Each inspected joint can be associated with an image, defect classification, dimensional measurement, and time stamp. This creates a useful digital quality record for manufacturing control.

### **Comparative Evaluation of Conventional and Artificial-Vision Inspection:**

A comparative experimental framework can be established using a series of GMAW welded specimens containing intentionally varied surface conditions. Welding parameters may be adjusted to produce representative undercut, porosity, excessive reinforcement, spatter, and bead-width irregularity. Each specimen is first evaluated by qualified visual inspectors according to predefined acceptance criteria. The same specimens are subsequently photographed under controlled illumination and analyzed using an artificial-vision algorithm.

Comparison metrics should include detection accuracy, false-positive rate, false-negative rate, repeatability, inspection time, measurement consistency, and documentation capability. Human inspectors may perform particularly well when surface conditions are complex or ambiguous. For example, contamination, discoloration, or grinding marks may be correctly identified as non-defect conditions through contextual reasoning. Artificial vision may outperform manual inspection in repeated dimensional measurements. Once the camera is calibrated, bead width and geometric deviation can be measured rapidly and consistently. In an illustrative comparison, conventional visual inspection may achieve strong overall defect recognition but demonstrate greater variation among inspectors. Artificial vision may show improved repeatability and shorter average inspection time, particularly when evaluating standardized joint geometries. The proposed graph for this study compares illustrative defect-detection percentages for both techniques across five surface discontinuity categories. These values are conceptual and should be replaced with real experimental results when available. Several factors may influence artificial-vision performance. Excessive glare can obscure weld edges, while poor contrast can reduce segmentation accuracy. Camera perspective can distort geometric measurements if calibration is inadequate. Therefore, artificial vision requires more controlled environmental conditions than human inspection. The most important conclusion from comparative analysis is that both methods provide complementary advantages. Human inspectors provide flexibility and contextual judgment, while artificial vision provides speed, consistency, quantitative measurement, and digital traceability.

#### **Industrial Integration, Limitations, and Future Development:**

Artificial vision is especially suitable for production environments in which joint geometry and camera position remain relatively consistent. Automotive assembly lines, robotic welding cells, and repetitive fabrication operations provide favorable conditions for automated inspection because imaging equipment can be installed at fixed positions. A vision system can inspect each completed weld immediately after production. Welds classified as acceptable can continue through manufacturing, while uncertain or defective welds can be diverted for manual inspection. This hybrid approach reduces inspector workload without removing human expertise from final quality decisions. Artificial vision may also contribute to process optimization. If a system identifies a gradual increase in bead-width variation or spatter, manufacturing personnel can investigate welding parameters before severe defects occur. Inspection therefore becomes not only a quality-control activity but also a source of process-monitoring data. The primary limitation of artificial vision is its dependence on controlled imaging. Reflections, smoke residues, scale, surface oxidation, shadows, and inconsistent camera positioning can influence classification. Three-dimensional weld geometry can also be difficult to evaluate using conventional two-dimensional images. Future systems may address this limitation through laser profilometry, structured-light imaging, stereo vision, and three-dimensional scanning. These methods can measure weld reinforcement, undercut depth, and surface geometry more accurately than conventional two-dimensional imaging.

Deep-learning models also offer significant potential. Instead of relying exclusively on handcrafted thresholds, neural networks can learn defect patterns from large datasets. Transfer learning can reduce the amount of training data required, although industrial implementation still demands rigorous validation. Explainable artificial intelligence represents another important future area. Quality-control personnel may require not only a pass/fail decision but also information explaining why a weld was classified as defective. Systems that highlight the suspected defect region can improve trust and facilitate inspector verification. Integration with robotic welding systems could ultimately establish closed-loop quality control. Inspection results could be used to adjust welding current, voltage, travel speed, or torch trajectory during subsequent welds. Such integration would move manufacturing toward intelligent self-correcting production. Nevertheless, artificial vision should not be interpreted as a complete replacement for nondestructive examination. Visual techniques are limited primarily to surface conditions. Internal defects such as lack of fusion, incomplete penetration, internal porosity, and subsurface cracking may require radiographic, ultrasonic, magnetic-particle, or penetrant testing depending on material and application.

#### **Summary**

This study presented a comparative analysis of conventional visual inspection and artificial-vision-based inspection for GMAW welded joints. The investigation focused on visible surface characteristics including undercut, surface porosity, excessive reinforcement, underfill, spatter, bead-width variation, and visible cracking. Conventional visual inspection remains one of the most practical and widely used weld-quality assessment methods. Its principal advantages include flexibility, low equipment requirements, immediate interpretation, and the ability of experienced inspectors to evaluate complex or unexpected surface conditions. However, manual visual inspection is influenced by human factors such as experience, fatigue, visual acuity, interpretation, and environmental conditions. These factors can reduce repeatability, particularly in high-volume manufacturing environments. Artificial vision offers a complementary approach by converting weld appearance into digital information that can be measured and classified objectively. A typical system uses controlled image acquisition, preprocessing, segmentation, feature extraction, and defect classification.

Machine-vision systems provide important advantages in repeatability, processing speed, dimensional measurement, and digital documentation. Automated storage of images and inspection results can improve manufacturing traceability and quality management. Nevertheless, artificial vision performance depends strongly on camera calibration, illumination, image resolution, surface condition, and algorithm robustness. Reflective metallic surfaces and changing environmental conditions can reduce detection reliability. The comparison indicates that neither technique is universally superior. Conventional inspection provides contextual intelligence and adaptability, whereas artificial vision provides standardized quantitative assessment. The strongest industrial strategy is therefore a hybrid inspection model in which automated vision performs rapid screening and measurement while qualified personnel evaluate uncertain cases and make final acceptance decisions. Future developments in deep learning, three-dimensional imaging, laser scanning, robotic inspection, and closed-loop manufacturing control are expected to increase the capabilities of automated weld inspection. Such technologies can transform visual examination from a purely post-process activity into an integrated element of intelligent manufacturing and continuous quality assurance.

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