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Article

Online Detection of Surface Defects in Continuous Cast Billets Based on Multi-Information Fusion Method

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Abstract

Surface defects in high-temperature continuous cast billets are critical factors affecting the quality of steel products. Owing to high-temperature radiation, heavy dust contamination, varying billet specifications, and background interference from oxide scales and water stains, existing online surface defect detection technologies for high-temperature continuous cast billets still suffer from limitations including high false-positive rates, inefficient identification of pseudo-defects, and the inability to simultaneously detect three-dimensional (3D) depth information alongside two-dimensional (2D) features. To solve these problems, this paper proposes a multi-dimensional online detection technology for surface defects in high-temperature continuous cast billets based on multi-information fusion. A four-channel multispectral image sensor and a corresponding three-light-source imaging system were developed. Furthermore, a defect sample augmentation method, a deep learning-based 2D recognition method, and a photometric stereo-based 3D reconstruction method were designed to mitigate problems of low detection accuracy and poor robustness caused by sample imbalance among different defect types. Finally, industrial applications were conducted on large-section continuous cast billets, beam blanks, and billets during the grinding process. According to the surface defect detection requirements of different continuous cast billets, multispectral multi-information fusion and traditional 2D defect imaging methods were adopted respectively. The results demonstrate high-precision online detection of surface defects in continuous cast billets, with favorable practical application effects.

Keywords: continuous casting billets; surface defects; deep learning; photometric stereo; multi-dimensional; online detection

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1. Introduction

Steel materials are renowned for their low cost, high strength, excellent ductility, and superior processability [1], and their derived products are widely used in various aspects of daily life, such as high-rise buildings, automobiles, household appliances, and transportation infrastructure. As a cornerstone of modern industries—including construction, infrastructure engineering, manufacturing, tool and equipment production, energy and transportation, and daily commodity manufacturing—the quality of steel materials, and particularly quality control during the production and manufacturing process, directly affects user experience and safety in daily life and has thus attracted widespread attention.

According to incomplete statistics, annual economic losses caused by surface quality issues in steel materials amount to tens of billions of US dollars [2]. This necessitates close attention to the origins and evolution of surface quality defects during high-temperature metallurgical production processes.

The continuous casting process [3], as the intermediate link between smelting and rolling, is the primary source of raw materials for all subsequent semi-finished and finished rolled steel products [4]. The level of online detection and feedback control of surface quality in the continuous casting stage directly determines the final surface quality of steel products [5–9]. Thus, numerous scholars have conducted extensive research on imaging and identification methods for surface defects in continuous casting billets under high-temperature conditions.

Ghorai et al. investigated defect detection methods for hot-rolled flat steel products [10], while Saleh et al. studied subsurface defect detection in concrete structures using two-dimensional continuous wavelet transform [11]. Fu proposed a quality inspection method for continuous casting billets based on infrared flaw detection and two-dimensional (2D) imaging [12], and Qiu developed a defect classification approach for continuous casting slabs using pulsed eddy current technology combined with spectral analysis and wavelet decomposition [13]. Obeso [14], Alvarez [15], Zhao [16], Zhang [17], and Ma [18] also carried out research on traditional 2D deep learning-based classification methods for surface defects in continuous casting slabs. However, due to the harsh high-temperature working environment and interference from complex backgrounds such as oxide scales, the aforementioned studies have failed to effectively improve the recognition accuracy for surface defects in high-temperature continuous casting billets. With the rapid advancement of deep learning technologies, some researchers have enhanced the accuracy of surface defect recognition against steel backgrounds through strategies such as model lightweighting, targeted focus on defect features, local adoption of multi-layer convolutional structures, and the integration of attention mechanisms [19–23].

Meanwhile, the three-dimensional (3D) depth information of surface defects in high-temperature continuous casting billets is critical for accurately evaluating defect severity and providing precise guidance for subsequent grinding processes. Traditional 2D defect detection methods are thus unable to meet the 3D depth detection requirements for surface defects in high-end steel grades. In response, some researchers have explored photometric stereo-based 3D reconstruction methods for surface defects [24–26]. Nevertheless, as photometric stereo methods rely on the coordinated operation of multiple light sources and imaging systems, their detection speed fails to satisfy the real-time requirements of online inspection for high-temperature continuous casting billets [27].

In view of the above challenges, this paper proposes a multi-dimensional online detection technology for surface defects in high-temperature continuous casting billets based on multi-information fusion. A four-channel multispectral image sensor and a corresponding three-light-source imaging system were developed. Additionally, a defect sample augmentation method, a deep learning-based 2D defect recognition method, and a photometric stereo-based 3D defect reconstruction method were designed to address the low detection accuracy and poor robustness caused by sample imbalance across different defect types. Finally, industrial application tests were performed on large-section continuous casting billets, beam blanks, and billets during the grinding process. Based on the specific surface defect detection requirements of different inspected objects, multispectral multi-information fusion and traditional 2D defect imaging methods were employed respectively. The experimental results confirm that the proposed technology enables high-precision online detection of surface defects in continuous casting billets, exhibiting excellent practical application effects.

2. Key Challenges

2.1. Detection Requirements

According to surface detection requirements and cross-sectional morphologies encountered during production, the products can be divided into four main categories: large-section billets, multi-strand billets from a single caster, beam blanks, and continuous casting billets during the grinding process. The cross-sectional shapes of these billet types are presented in Figure 1.



Figure 1. The cross-sectional shapes of different billet types.

Large-section billets facing major detection challenges due to variations in alloy composition and carbon content. As temperature decreases, a thick oxide scale forms on the surface, which severely obscures underlying defects and hinders effective identification. Multi-strand billets produced by a single-caster feature complex and variable dimensions. Moreover, the narrow spacing between strands requires full four-surface inspection within a confined space, accompanied by harsh environmental conditions including high temperature, dust, and water vapor.

Beam blanks exhibit complex surface profiles, characterized by a thin web and relatively thick flanges. Cracks and other typical surface defects frequently occur near the curved transition regions. To reduce surface defects, a high-temperature flame cleaning process is often adopted to remove interfering oxide scales. This step is particularly critical for high-added value products, which demand extremely high surface quality. As a result, the ground billet surface typically shows considerable roughness and unevenness, making online detection of surface defects—especially minor ones—on highly reflective ground surfaces extremely important.

2.2. Detection Challenges

For a long time, surface defect detection for continuous casting billets has mainly relied on manual inspection, which could generalize into two categories.

The preferred option method is online inspection, in which workers directly observe the surface of red-hot billets after cutting. Due to high temperatures, workers cannot approach the billets closely, leading to a very limited detection range that cannot achieve full coverage. In addition, some minor defects, especially fine cracks, are easily overlooked. The harsh working environment and high labor intensity also make it difficult to maintain stable and continuous inspection.

The traditional method is offline inspection, which requires removing billets from the production line and cooling them before manual examination. Although this method improves visibility, it does not support hot charging and direct rolling. Furthermore, it cannot realize real-time identification of surface defects or provide a rapid response mechanism. This may also cause the continuous occurrence of defects and production shutdowns, resulting in substantial economic losses.

The main challenges of online surface defect detection for high-temperature continuous casting billets are summarized as follows:

Firstly, continuous casting billets have various specifications and types. In addition, beam blanks and ground continuous casting billets usually have uneven and complex

surfaces. Therefore, achieving high-definition imaging under high dynamic conditions and diverse specifications is one of the primary challenges for real-time online defect detection.

Secondly, owing to the strong surface radiation of high-temperature billets, images captured by conventional white-light sources and cameras often suffer from low contrast between defects and the background. Improving imaging quality thus becomes the second major challenge affecting detection accuracy.

Thirdly, the surfaces of high-temperature billets are affected by complex background interference, such as oxide scales and water stains. In particular, edges of oxide scales can resemble crack edges and are difficult to distinguish by using conventional image features. Accurate defect identification under strong interferences from oxide scales and water stains therefore constitutes the third key challenge.

Fourthly, the collection and verification of defect samples for high-temperature billets are difficult. Defects observed in images cannot be directly compared with those on hot billets in real time. Once billets cool down, defect features may change or be covered by oxide scales. Consequently, rapid and accurate acquisition of defect samples is another critical challenge for reliable surface defect detection.

Given the unique characteristics of continuous casting billet inspection, comprehensive considerations must be given to imaging system design, algorithm development, and defect sample collection methods.

2.3. Solution Strategies

This study focuses on multiple difficulties encountered in high-temperature continuous casting billet inspection, including challenges in high-definition imaging, complex and variable product specifications, strong interference from surface oxide scales, requirements for four-sided inspection, high imaging background noise, limited defect sample volumes, and low defect detection and classification accuracy. This paper proposes three aspects to solve these problems: high-contrast imaging design, multi-information fusion detecting, and defect recognition algorithm modeling.

(1) Development of short-wave illumination technology suitable for high-temperature continuous casting billets.

High-temperature environments promote the formation of oxide scales and other contaminants on billet surfaces, which severely interfere with imaging. By developing a novel illumination system based on a 450 nm blue semiconductor laser source, imaging contrast and clarity are significantly improved, effectively suppressing the interference caused by high temperatures and oxide scales.

(2) Development of multispectral-based large-depth-of-field dynamic imaging technology for high-temperature continuous casting billets.

High-temperature continuous casting billet surfaces frequently exhibit small-scale dimensional defects such as pores and cracks, whose accurate detection is essential for high-quality production. However, such minor defects are often masked by complex interferences including high temperatures and oxide scales, creating great difficulties for surface imaging. To solve these problems, this paper proposes an integrated imaging strategy that simultaneously acquires and synchronizes 2D grayscale information, 3D depth data, and surface temperature distribution. Using a high-definition variable-cross-section imaging method with multi-angle and large-depth-of-field capability, the billet surface is imaged from multiple perspectives and depth ranges to obtain comprehensive surface information.

(3) Development of a multi-information fusion-based multidimensional defect detection model for high-temperature continuous casting billets.

Traditional deep learning algorithms facing limitations in billet defect detection, including difficulties in extracting discriminative features and unsatisfactory performance caused by insufficient training samples. To solve these issues, this study develops a multidimensional defect detection model based on multi-information fusion for high-temperature continuous casting billets.

The model integrates temperature measurement with 2D image defect detection algorithms to establish a real-time pseudo-defect identification method, which effectively eliminates background interference from oxide scales, water stains, and other sources. A data augmentation technique based on neural style transfer learning is also introduced, which converts original images into new samples with specific styles to enlarge the dataset and reduce overfitting caused by limited data, thus solving the small-sample problem.

In addition, a 3D depth recognition method for billet surface defects is developed based on multispectral photometric stereo technology. This method enables fast and robust identification of various surface defects, including pores, slag inclusions, and cracks.

3. Technical Approaches

3.1. Short-Wave Multispectral Imaging

One of the most critical factors enabling high-accuracy identification of surface defects is high contrast between defects, oxide scale, and the normal surface background in captured images. In other words, the visual difference between defects and defect-free regions must be sufficiently distinct to provide a reliable imaging foundation for subsequent algorithmic recognition. Typically, the surface temperature of high-temperature continuous casting billets at the inspection station ranges from approximately 750 °C to 1200 °C. Such high temperatures introduce severe interference for high-definition imaging, which is further compounded by complex on-site disturbances such as moisture and dust. Therefore, designing a high-performance illumination system capable of supporting high-definition imaging has become one of the key enabling technologies for online surface defect detection in high-temperature continuous casting billets.

The first-generation illumination system for high-temperature billet imaging employed a white light source. This system performs adequately for billets with relatively clean surfaces but provides insufficient contrast for high-temperature billets suffering from strong interference, such as water stains and oxide scales. The second-generation system adopted a green light source, which is generally suitable for billets with flat surfaces and negligible curvature variations, such as large-section billets. However, its performance degrades significantly when inspecting irregular billets with convex or concave surface features.

Our research team developed a blue-light imaging system based on semiconductor lasers. Compared with green light sources, this system delivers clearer imaging on irregular surfaces and higher sensitivity for tiny defects. A comparison of imaging performance under the short-wave imaging scheme is presented in Figure 2. In addition, by physically separating the semiconductor laser from the optical probe, the design reduces heat accumulation inside the high-temperature imaging module and extends the service life of the detection system.

3.2. Multispectral Image Sensing System

Based on the preceding analysis of challenges in surface defect identification for high-temperature continuous casting billets, achieving high-contrast, high-definition defect imaging under complex interferences—including high-temperature radiation, surface scale, and water stains—remains a critical technical challenge. In particular, the edges of oxide scales closely resemble those of longitudinal cracks, making them difficult to distinguish by using conventional image features alone. Moreover, oxide scales are widely distributed

across the billet surface and frequently lead to high false-alarm rates in defect identification, severely impairing detection accuracy.

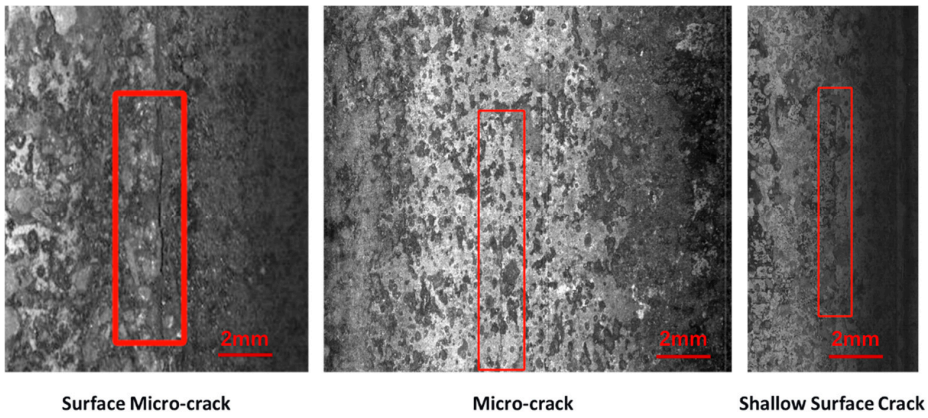


Figure 2. The imaging effects under the short-wave imaging process.

Previous studies have shown that the surface temperature of oxide scale is approximately 100 °C to 150 °C lower than that of both normal surfaces and real defects [28]. Therefore, if surface temperature distribution can be obtained simultaneously during imaging, it becomes feasible to effectively discriminate oxide scales from genuine defects based on temperature differences. On the other hand, for billets requiring high-precision surface defect detection and depth information to guide subsequent grinding and treatment, acquiring the 3D depth information of surface defects is essential to realize three-dimensional online defect detection.

In summary, high-temperature billet surface imaging must simultaneously capture 2D information, 3D depth information, and surface temperature distribution. Accordingly, this study designs a multispectral fusion imaging system composed of a multispectral image sensor, a tricolor light source, and an imaging control unit.

The multispectral image sensor integrates four functional modules: three visible-light channels and one far-infrared channel, as illustrated in Figure 3. The three visible-light imaging modules are equipped with narrow-band filters corresponding to the R, G, and B wavelengths to achieve band-resolved imaging. These modules are primarily responsible for high-definition image acquisition of the target, ensuring key performance indicators including field of view, focal length, and relative aperture, while satisfying imaging quality requirements for distortion and spot size. The far-infrared thermal imaging module measures the surface temperature of continuous casting billets, with a measurement range covering temperatures above 1200 °C, allowing for identification of fine temperature distributions.

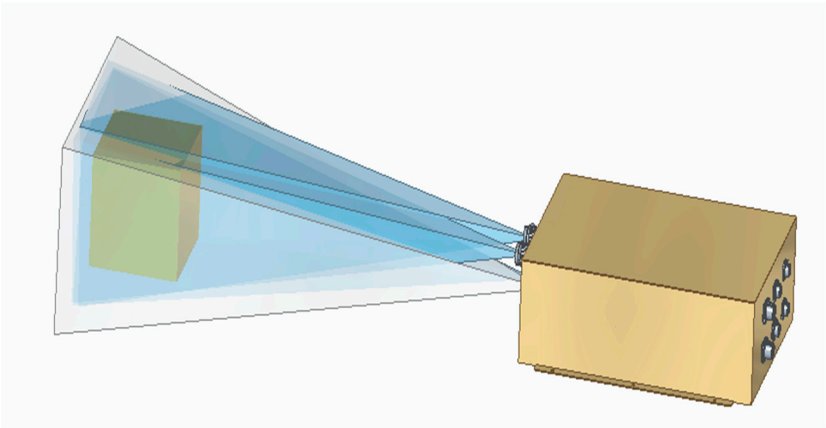


Figure 3. The mechanical structure diagram of the four-channel multispectral camera.

An FPGA-based image acquisition circuit is configured to synchronize image capture from the three visible-light imaging modules and the far-infrared thermal imaging module and to transmit image data as commanded by the host system. The tricolor light source consists of three separate R, G, and B planar illumination units arranged at different angular positions. The imaging control system manages precise synchronization between the light sources and the camera imaging sequence.

A complete imaging cycle consists of four coordinated acquisition sequences: the R, G, and B light sources are activated sequentially, with their corresponding visible-light modules capturing images in separate frames; meanwhile, the infrared module performs independent temperature imaging. This cycle generates four core images:

- The R image is used for the 2D defect recognition model;
- The G and B images are used for the photometric stereo-based 3D defect reconstruction model;
- The infrared image is used for the temperature recognition model.

4. Multi-Information Defect Recognition Model

4.1. Adversarial Learning-Based Sample Augmentation Method for Surface Defects

With recent research progress in deep learning methods, an increasing number of deep learning-based image augmentation techniques have been applied in industry detection. However, deep learning algorithms require a large number of real samples to achieve satisfactory model recognition capability and generalization performance. Due to the limited number of surface defects, such as cracks, on continuous casting billets in high-temperature conditions, the available data is insufficient to meet the training requirements of the model. Generally, sample augmentation methods are employed to increase the number of samples for certain types of defects, using generative adversarial networks to directly synthesize domain-specific images or perform neural style transfer across different domains and using meta-learning-based data augmentation. Among these, neural style transfer-based data augmentation has demonstrated effectiveness in various image processing fields, including medicine and materials science.

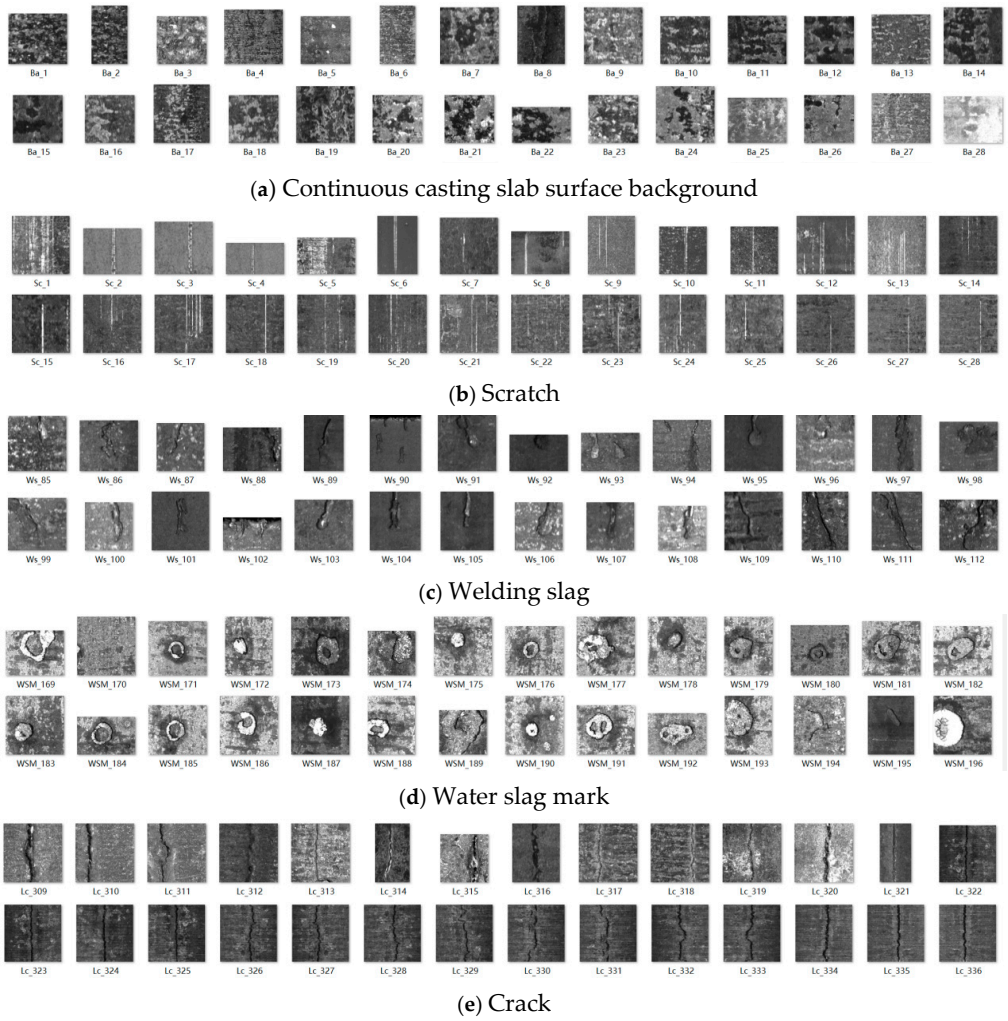
Studies have shown that in material image segmentation tasks, style transfer networks can simulate and generate synthetic images with textures similar to real training samples based on material simulation images. By incorporating such synthetic images, only 35% of the original training dataset is required to achieve performance comparable to using 100% of the original training data. Therefore, our team adopted an adversarial learning-based neural style transfer algorithm to fully exploit shared features among similar data types, thereby augmenting limited surface defect samples to a sufficient quantity. This approach effectively expands the dataset of continuous casting billet defects.

In this study, a DCGAN (Deep Convolutional Generative Adversarial Network) is used as the basic architecture for both the generator and discriminator. A DCGAN is a generative adversarial network variant based on convolutional neural networks. As an improved version of the standard generative adversarial network, it is mainly used for image generation. Compared with traditional generative adversarial networks, a DCGAN optimizes the network structure and can generate more realistic images. Similarly to conventional generative adversarial networks, a DCGAN consists of two components: a generator and a discriminator, both based on convolutional neural networks.

The generator uses deconvolution layers for up sampling, converting low-resolution inputs into high-resolution output images. In contrast, the discriminator uses convolutional layers for feature extraction and outputs a scalar value representing the authenticity of the input image. Cross-entropy loss is adopted for both the generator loss and discriminator loss. The generator loss measures the discrepancy between generated images and real

images, while the discriminator loss evaluates its ability to distinguish real images from fake ones produced by the generator.

Using the above method, a new dataset for high-temperature continuous casting billets is constructed and used to train classifiers. Samples of different defect types including continuous casting slab surface backgrounds, scratches, welding slags, water slag marks and cracks are presented in Figure 4. This dataset effectively improves the robustness of the recognition model and alleviates the low detection rate caused by imbalanced sample distributions across defect categories.



(**a**) Continuous casting slab surface background

(**b**) Scratch

(**c**) Welding slag

(**d**) Water slag mark

(**e**) Crack

Figure 4. Effect of sample augmentation for high-temperature continuous casting billet surface defects.

4.2. Deep Learning-Based 2D Defect Recognition Model

At present, with a sufficiently large number of various surface defect samples, deep learning models represented by the YOLO series have achieved promising recognition and classification performance in defect identification. Therefore, this study conducts adaptive research on surface defect recognition for high-temperature continuous casting billets, focusing on two aspects: algorithm-level improvements to the YOLO series and post-deployment optimization in practical applications.

On the one hand, an attention mechanism is integrated into YOLO-based recognition algorithms. The Convolutional Block Attention Module or Coordinate Attention is embedded into the backbone or neck network, enabling the model to focus on regions with texture variations on the high-temperature billet surface while suppressing interference

from uniform high-temperature backgrounds. For continuous casting billets, defects typically appear as local texture anomalies, and attention mechanisms help capture such fine details.

To address large cross-scale differences between small defects such as roll marks and long narrow longitudinal cracks, the expressive power of multi-scale features is enhanced. The feature pyramid structure is improved by increasing the utilization of shallow features and introducing Adaptive Spatial Feature Fusion to dynamically learn weights for features at different scales. For elongated crack defects, Deformable Convolutional Networks are incorporated to adapt convolution kernels to defect shapes, thereby improving sensitivity to irregular defects.

Considering the directional characteristics of defects such as cracks and scratches on continuous casting billets, an angular penalty term is added to the bounding box regression loss, or rotated bounding box detection is used to strengthen shape-aware loss for defects. For hard-to-identify defects such as cracks, a lightweight preprocessing network is designed to perform temperature field normalization or thermal radiation correction on input images based on multi-information fusion temperature-aware results, reducing the influence of temperature variations on surface texture representation.

Meanwhile, for pseudo-defects and real defects that are difficult to distinguish under high-temperature interference, Focal Loss or GHM loss is adopted to reduce the weight of simple negative samples in uniform high-temperature regions, allowing the model to focus on hard samples. To meet real-time detection requirements, lightweight techniques including model pruning and quantization are applied to balance model compactness and real-time performance in the 2D defect recognition model.

On the other hand, after the locally trained model is deployed online, inter-frame information is utilized for continuously moving high-temperature billets. Inter-frame stability constraints are introduced to improve the positional continuity of defects across adjacent frames, effectively reducing false positives. An adaptive threshold mechanism is designed to adjust dynamically according to the overall image noise level, avoiding missed or false detections in frames with severe interference.

An online adaptive learning mechanism is established after model deployment. New samples are automatically added to a buffer pool when operators confirm or correct detection results. Periodic incremental learning or online fine-tuning is performed to adapt the model to variations on the production line. In this paper, four high-performance NVIDIA GeForce RTX 4090 graphics cards, which are built on the Ada Lovelace architecture and equipped with 24 GB of GDDR6X VRAM, are applied for model training and on-site inference.

4.3. Photometric Stereo-Based 3D Defect Recognition Model

Photometric stereo is a branch of the classical 3D reconstruction method known as Shape-From-Shading. It involves capturing images with varying photometric information by changing the position or spectrum of the light source while keeping the relative positions of the camera and the object unchanged. The surface normal of the object is then recovered based on an imaging photometric model. Since photometric stereo performs calculations at the pixel level, it is particularly suitable for high-frequency signals and excels at preserving fine surface details.

Traditionally, photometric stereo-based 3D reconstruction theoretically requires at least three non-collinear light sources to accurately determine surface normal and reconstruct the 3D surface. However, increasing the number of light sources also complicates the system structure. Therefore, this study develops a photometric stereo 3D measurement method using only two light sources, as illustrated in Figure 5.

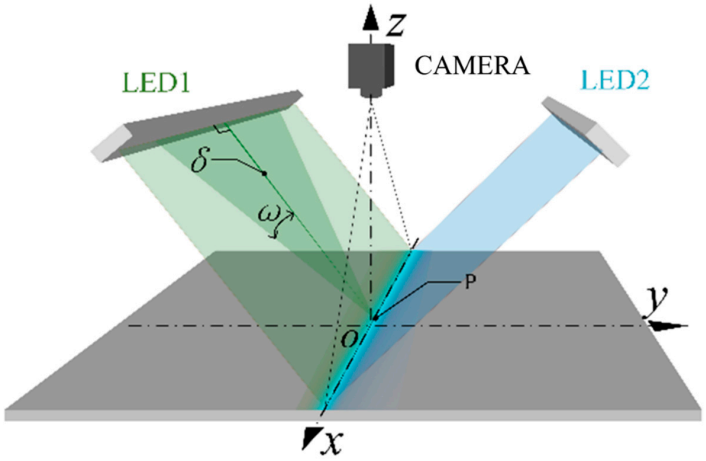


Figure 5. Schematic diagram of the dual-light-source photometric stereo 3D detection imaging.

LED1 and LED2 are two alternately lit LED line lights, and the camera is a line-scan camera positioned perpendicular to the measured plane. LED1 and LED2 are symmetrically arranged on both sides of the camera's optical plane at the same height above the measured surface. Their incident light converges on the measured plane and remains collinear with the camera's optical plane. Image acquisition by the camera is fully synchronized with LED1 and LED2.

As LED1 and LED2 illuminate alternately, the camera performs alternating line-scan imaging. When the high-temperature continuous casting billet passes through the measurement area, the system first sends a trigger signal to LED1 and the camera. LED1 illuminates while the camera exposes, capturing the object image under LED1 lighting, corresponding to the odd scan lines. The system then triggers LED2 and the camera: LED2 illuminates and the camera exposes, capturing the image under LED2 lighting, corresponding to the even scan lines.

Once the camera captures the preset number of lines, the odd and even lines can be extracted to form odd and even fields, respectively. The odd field corresponds to the object image under LED1 illumination, and the even field corresponds to the image under LED2 illumination. Due to the high acquisition frequency of the line-scan camera, the time interval between triggering odd and even lines is extremely short, so the offset between them can be neglected. Thus, the odd and even fields can be regarded as corresponding to the same position on the measured object, satisfying the requirements for photometric stereo 3D reconstruction.

The 3D reconstruction and detection workflow of the dual-light-source photometric stereo method is as follows:

First, system calibration is performed for the dual-light-source hardware setup. A standard diffuse reflection whiteboard is used to accurately measure or calibrate the direction vectors of the two light sources relative to the camera.

Then, image acquisition is carried out, ensuring that the object and camera remain essentially stationary during the two exposures.

Image preprocessing is performed, including denoising and non-uniform illumination correction (flat-field correction), followed by selection of a flat reference background region.

Next, calculations are performed for the pseudo-normal vector field, reference region normalization, gradient field computation, and surface integration.

Finally, a height map of the surface texture is obtained, supporting intuitive visualization of defect depths.

In summary, using the dual-light-source photometric stereo method for 3D reconstruction of high-temperature continuous casting billet surfaces enables the derivation of

y-direction gradient values via photometric stereo even with only two light sources. This provides critical support for obtaining depth information on the surface of high-temperature continuous casting billets.

5. Online Surface Defect Detection Equipment and Field Application Cases

The online surface defect detection system for high-temperature continuous casting billets described above integrates multi-information fusion based on two-dimensional visual features, three-dimensional depth information, and surface temperature data. This technology provides critical guidance for quality inspection of high-value continuous casting billets. However, it still faces challenges such as relatively high implementation costs and varying application requirements across different inspection scenarios.

This section elaborates on the features and performance of the online surface defect detection technology for high-temperature continuous casting billets in three typical application scenarios: large-section billets, beam blanks, and continuous casting billets during the grinding process. Among these configurations, the multi-information fusion scheme is adopted for large-section billets, while only top-surface inspection is applied for beam blanks and billets during grinding, which is sufficient to meet their respective quality requirements.

5.1. Large-Section Billets

The surface defect detection system for large-section continuous casting billets mainly consists of the following components: multispectral image sensors, illumination sources, integrated protective enclosures, acquisition controllers, environmental control systems, servers, network switches, and user terminals. The detection units for the top, bottom, left, and right surfaces of the high-temperature billet include both illumination sources and multispectral image sensors. Each multispectral sensor is equipped with three light sources (R, G, and B), arranged in a triangular layout surrounding the sensor.

The imaging system captures surface image information of the moving billet and transmits the data to a parallel computer processing system for analysis. This system comprises multiple client computers, each connected to an individual camera to receive and process the corresponding image data. This configuration ensures that images from each multispectral camera are processed by a dedicated computer, enabling parallel computing across multiple hosts and significantly improving the overall data processing capability.

When an abnormality is detected on the billet surface, the system stores the image in a buffer for further analysis. Using image processing and pattern recognition techniques, the system automatically identifies defects on the top, bottom, left, and right surfaces. Defects are classified into predefined categories according to the built-in classification scheme, and different alarm strategies are triggered based on defect severity. All image processing and pattern recognition tasks are executed on the client computers. The surface defect detection system for large-section high-temperature continuous casting billets is shown in Figure 6.

After processing and analysis by the parallel computing system, the defect results are transmitted to the server. Since large defects may extend across images captured by different cameras, the server merges these partial results to generate a complete defect distribution map of the entire billet, supporting comprehensive surface quality evaluation. Meanwhile, the server archives the billet defect distribution information in a database for storage and traceability.

The server connects to multiple console terminals for displaying and recording defect images and data. The surface detection system interfaces with the billet production line automation system and process control computer to obtain key production data, including

billet ID, production status, steel grade, casting speed, width, and length. By integrating this information with surface inspection results, a complete quality record is established for each billet. Figure 7 shows four-channel surface images of a high-temperature continuous casting billet acquired by the multispectral imaging system.



Figure 6. Schematic diagram of the surface defect recognition device for large-section high-temperature continuous casting billets.

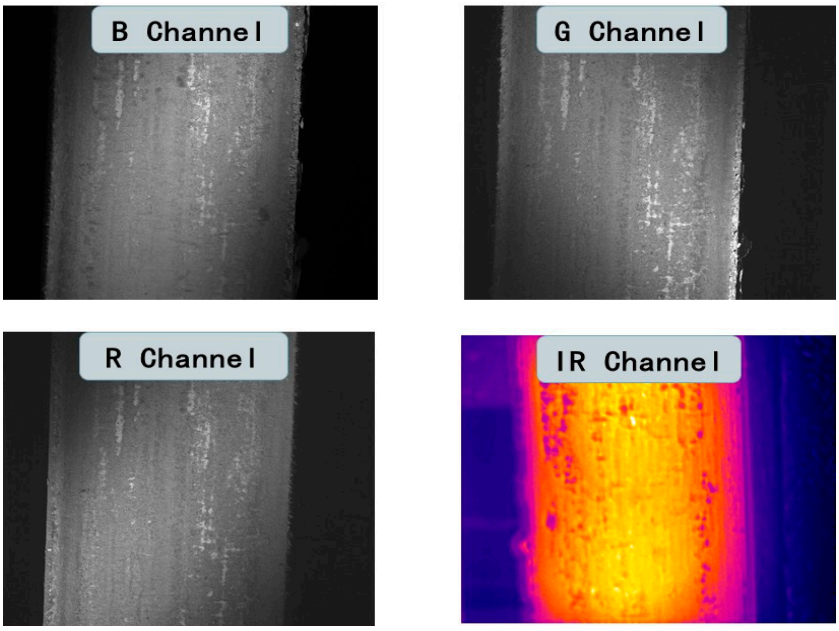
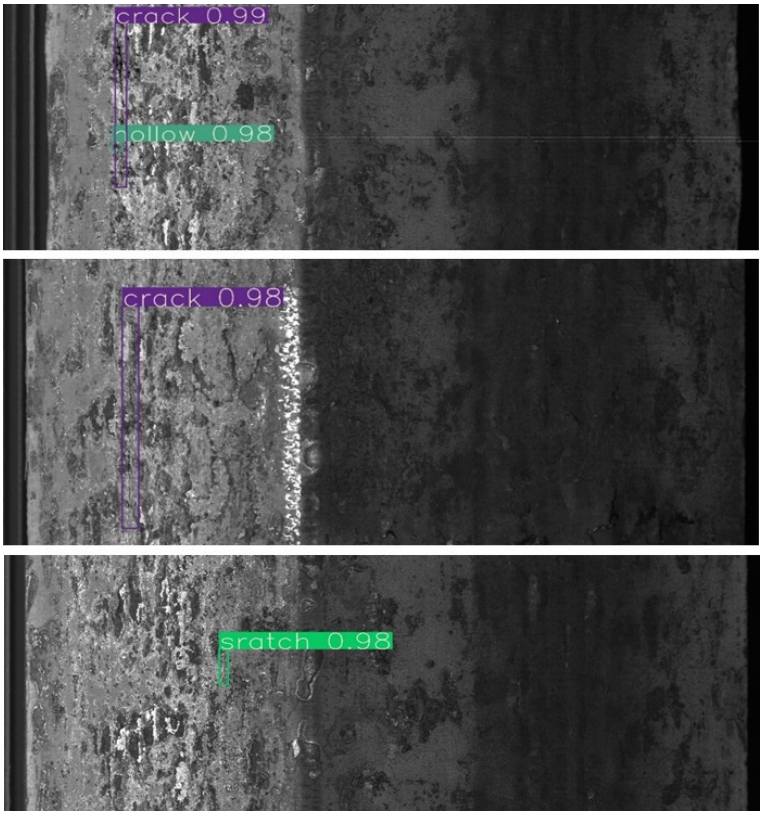


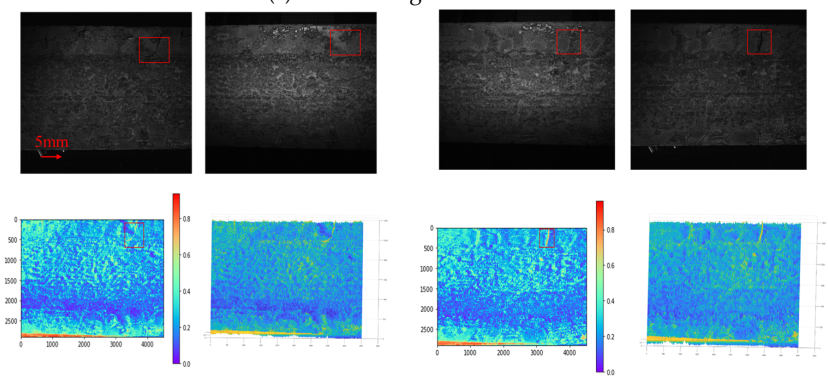
Figure 7. Multi-channel images acquired by the multispectral camera.

A dual-light-source photometric stereo method is used to estimate the surface depth distribution of the billet. Temperature measurement is applied to analyze surface temperature differences, helping to identify regions covered by oxide scale. Finally, temperature information, depth data, and 2D deep learning-based defect recognition results are fused to distinguish between pseudo-defects and real defects.

Figure 8 presents the 3D reconstruction results and defect recognition performance for large-section billet surfaces. The meanings represented in Figure 8b by the colors are shown on the right side of each figure. The redder the color, the greater the depth; the bluer the color, the smaller the depth. The detection rates for typical surface defects including cracks, pits, and scratches reach 95.5%, 97%, and 96.4%, respectively, with corresponding classification accuracies of 91%, 95.5%, and 90.8%.



(**a**) Defect recognition results



(**b**) 3D reconstruction result

Figure 8. 3D reconstruction results based on photometric stereo and defect recognition results for high-temperature continuous casting billets.

5.2. Beam Blanks

The cross-section of a beam blank is relatively complex with prominent curvature transitions, and cracks frequently occur in these transition zones. Therefore, the online surface defect detection system for beam blanks adopts a conventional top-surface inspection architecture. The system comprises a blue laser line light source combined with two line-scan CCD cameras for image acquisition, while the left camera covers the right side of the billet, and the right camera covers the left side.

The line-scan CCD cameras are mounted above the inspected beam blank. Light from the source is projected onto the billet surface at a fixed angle, and the reflected light is collected by the cameras. The cameras scan transversely across the surface, converting the reflected light intensity into a grayscale signal. As the beam blank moves continuously, longitudinal scanning is achieved, and a complete two-dimensional image is reconstructed.

If a defect exists on the beam blank surface, it may absorb or scatter the incident light, causing a detectable change in the light intensity received by the camera. Line-scan cameras are widely used for inspecting continuous, uniformly moving products because they provide uniform imaging and good temporal continuity. However, since line-scan cameras capture only one row of pixels at a time, they impose relatively high requirements on illumination uniformity and stability.

Considering the characteristics and imaging difficulties of high-temperature beam blanks, a high-brightness laser line source with a wavelength of 450 nm is used for illumination. Compared with green lasers (typically 532–556 nm), the shorter wavelength of blue light is more favorable for detecting tiny defects. In addition, a 450 nm center-wavelength narrow-band filter is installed in front of each camera. This filter allows only the reflected laser light from the billet surface to pass through, effectively suppressing background radiation and improving image contrast.

The cameras are cooled by a water jacket with circulating water and equipped with a precision spiral adjustment mechanism. This design ensures a stable operating temperature and accurate optical alignment. The inspection system layout is shown in Figure 9, and its field of view covers the maximum width of beam blanks produced on site.



Figure 9. Surface defect detection equipment setup for beam blanks.

Defect recognition results for different types of surface defects on beam blanks are presented in Figure 10. The minimum detectable defect size is 0.2 mm. The detection rate for common surface defects exceeds 97.01%, and the classification accuracy reaches above 91.79%.

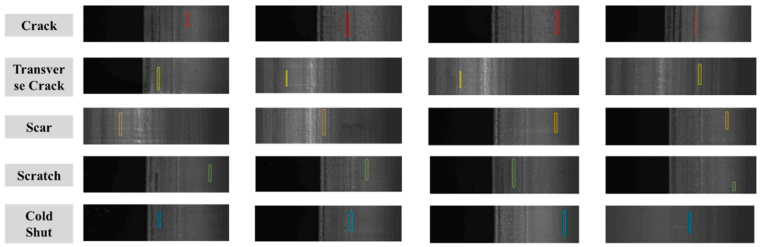


Figure 10. Recognition results of different types of surface defects of beam blanks.

5.3. Continuous Casting Billets During the Grinding Process

For high-valued steel products with stringent surface quality requirements, such as automotive outer panels and precision mold steels, the surface quality of continuous casting billets is critically important. Unresolved surface defects on the billet may be elongated and embedded into the material during subsequent hot rolling, remaining on the final product surface and leading to downgrading or even rejection. Therefore, after continuous casting and before hot rolling, the billet surface is usually treated to mechanically remove surface defects.

A smooth and clean billet surface after the grinding process could provide high-quality raw material for subsequent hot rolling. High-quality grinding can even reduce or eliminate surface defects at the head and tail regions that often form during hot rolling, significantly improving product yield. However, during the billet grinding process, it is necessary to detect defect positions in advance to accurately guide the grinding machine and minimize metal loss while ensuring complete defect removal.

Accordingly, the surface defect detection system for continuous casting billets developed in this study is applied for online defect identification on billets before grinding. Information including defect location, size, and type is transmitted to the grinding control system to support precise grinding operations.

Defect recognition results on the billet surface before grinding are shown in Figure 11. It can be seen that typical surface defects such as longitudinal cracks, transverse cracks, and scratches can be reliably identified.

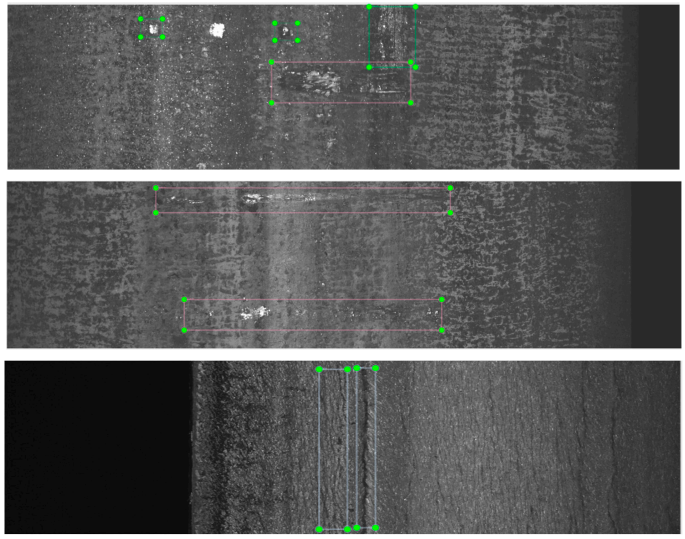


Figure 11. Defect recognition results on the surface of continuous casting billets during the grinding process.

6. Conclusions

This paper presents a multi-dimensional online detection technology based on multi-information fusion for surface defects in high-temperature continuous casting billets. A four-channel multispectral image sensor and a corresponding dual-light-source photometric stereo method were developed. To overcome the low detection accuracy and poor robustness caused by imbalanced datasets among different defect types, a defect sample augmentation method, a deep learning-based two-dimensional recognition method, and a photometric stereo-based three-dimensional reconstruction method were proposed and validated. Finally, industrial applications were implemented on large-section continuous casting billets, beam blanks, and billets during the grinding process. According to the surface defect detection requirements of different application scenarios, multispectral

multi-information fusion and traditional two-dimensional defect imaging methods were adopted accordingly. Experimental results show that the detection rates for typical surface defects including cracks, pits, and scratches all exceed 95%, with corresponding classification accuracies above 90%. High-precision online detection of surface defects in continuous casting billets is successfully achieved, and the proposed system demonstrates favorable and reliable performance in industrial applications. The research presented in this paper could help improve the recognition rate of surface defects on high-temperature continuous casting slabs. In response to the interference from complex backgrounds such as scale, a multi-information fusion imaging approach and detection method are designed to achieve high-precision recognition of surface defects on high-temperature continuous casting slabs. This lays a solid foundation for improving the surface quality of continuous casting slabs, thereby enhancing the stability and consistency of steel products.

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