On-Line Bleeds Detection in Continuous Casting Processes Using Engineering-Driven Rule-Based Algorithm

1 Introduction

Nowadays, continuous casting process has been widely adopted in the production of semifinished steel products worldwide, due to its inherent advantages of energy savings, enhanced productivity, higher yield, improved quality, and low costs. A continuous casting process is essentially a continuous solidification process, with the casting section encountering three entirely different cooling environments: a water-cooled mold, a series of cooling sprays, and the radiation zone before fully solidifying. Figure 1 shows a schematic of a continuous casting process. Detailed process description is presented afterwards.

Surface defects are critical quality concerns in a continuous casting process. In general, surface cracks normally pose more of a problem than internal cracks because, being exposed to air, the crack surfaces oxidize and do not reweld during rolling. One of the most common and critical billet surface defects is a bleed [1]. A bleed is a deep crack along and cross the longitudinal direction of a casting billet with an irregular pattern. As an example, the production of high quality wire rod requires billets that have a flawless surface. If billets contain bleeds during casting, bleeds will turn to deep cracks or catastrophic defects in a progressive rolling process. Semifinished billets with severe bleeds are ferociously responsible for "to-be-scraped" rolled products or wastes. Since the first step of trying to reduce bleeds is to successfully detect bleeds, on-line bleeds detection in continuous casting processes plays an important role in billets surface quality improvement. Most previous works have been devoted to revealing the mechanism of bleed formation [2,3]. Some qualitative suggestions have been proposed for bleed reduction through the casting process parameter optimization. Very few studies reported for on-line real time detection or process control of the bleeds during the continuous casting production.

In industry, visual inspection is a favorable nondestructive testing (NDT) method that has been extensively used to evaluate the condition or the quality of a product. With the development of advanced imaging technologies, vision sensors have been successfully adopted in the continuous casting process in the last few years. Those vision sensors provide more favorable methods in NDT comparing to an infrared scanning camera [4] and an X-ray based inspection system [5]. This is because radiography approaches are dangerous as X-ray and infrared rays are very hazardous to human beings. In addition, the X-ray and infrared cameras do not detect the surface quality of the casting parts clearly.

A vision sensing system has been developed recently to capture high resolution images of hot surface with temperatures around 1450°C [6,7]. The appearance of the images of the high temperature objects looks as if the object was at room temperature. With these visual images, automatic on-line detection of bleeds becomes possible. An illustrative vision-image from a continuous billet-casting process is shown in Fig. 1. However, there is no algorithm developed for automatic detection of bleeds in that visual image.

The challenges of automatic detection of bleeds lie in two main aspects: low signal-to-noise ratio with complicated background and irregular features of bleeds. In image processing, features refer to the specific structures in the image itself, ranging from a simple structure, such as points or edges, to a more complex structure such as objects or contours. Edge detection techniques, such as Sobel detectors [8] and optimal detectors [9], are not appropriate in this case because of their high sensitivity to noise. Irregular shape, area, and depth of bleeds bring significant challenges to feature-based detections [10,11]. Establishing feature pool through training sample images alone may not be feasible due to the irregular physical features of bleeds. Moreover, machine-learning approaches may not work effectively in this application due to a limited number of training samples (images containing bleeds). Under normal conditions, there should be few bleeds on billets that can be obtained for training purposes. In short, how to find the features of bleeds is the key not only to denoising but also to bleed detection. Thus, the idea emerges that it may be beneficial to extract some information from the engineering knowledge for building the feature pool for bleeds.

This paper proposes an engineering-driven rule-based detection (ERD) method for bleeds detection in a continuous casting of 7 in. square low-carbon steel billets at 1.5 m/min. The ERD integrates the physical knowledge of formation of bleeds covering metallurgical technology, metallurgical thermodynamics, and metallographic...
pressure analysis to facilitate defining, selecting, and describing the features that are essential for bleeds detection. The ERD also aims to introduce statistical methods driven by engineering knowledge in the feature detection.

2 Description of Images and Challenges in the Bleeds Detection

First of all, this section introduces the image specification and data structure. Then, challenges in the automatic bleeds detection are discussed. Finally, motivations for developing the ERD strategy are given.

2.1 Image Specification and Data Structure. The data of an image are a matrix with each element corresponding to one image pixel. The elements take integer values ranging from 0 gray-level to 255 gray-level, where 0 and 255 represent black and white, respectively. A matrix for one image containing $m \times n$ pixels is given in Eq. (1), where $p_{ij}$ is the gray-level of the pixel at the $i$th row and the $j$th column ($0 \leq p_{ij} \leq 255$).

$$
\begin{bmatrix}
  p_{1,1} & p_{1,2} & \cdots & p_{1,n} \\
  p_{2,1} & p_{2,2} & \cdots & p_{2,n} \\
  \vdots & \vdots & \ddots & \vdots \\
  p_{m,1} & p_{m,2} & \cdots & p_{m,n}
\end{bmatrix}
$$

(1)

2.2 Challenges in the Bleeds Detection. The features of a bleed are quite irregular in size, gray-level, shape, and location. Some images of bleeds with various patterns are given in Fig. 2. There are two major challenges in the bleeds detection. The first challenge is that it is difficult to develop the feature descriptions directly based on images, especially the training samples are limi-
ited. The second challenge comes from the strong noisy background in the images. The noises are deep oscillation marks, surface textures, and long strips of water sprays (refer to Fig. 1). The low signal-to-noise ratio makes the screening-out of bleed suspects troublesome not to mention extracting the bleed contours. Another undesirable condition is that the bleed is occasionally connected with deep oscillation marks (or overlap with water sprays). This leads to unreliable extraction of the bleed contours, which raises further challenges in feature description and feature detection of bleeds. Besides, there are many false positives in the image. Basically, the false positives are those deep oscillation marks that happen to have similar features with bleeds in shape and gray-level. The existence of false positives raises higher demand on feature design and selection. The feature pool developed should be able to not only screen out bleed suspects (i.e., real bleeds plus false positives) but also distinguish real bleeds from false positives. Some examples of the false positives are shown in Fig. 3, where the dark contours are all deep oscillation marks. The segments marked with arrows are image patterns of oscillation marks, but look close to real bleeds.

In the light of the above discussions, it is quite difficult to extract the features of bleeds through training based on image samples. An alternative detection approach is expected, which should be able to generate the feature pool fully utilizing a priori engineering knowledge and can well handle the irregularity of bleed patterns. Hence, an ERD algorithm is developed in this article, which will be discussed in Sec. 3.

3 Engineering-Driven Rule-Based Detection (ERD) Algorithm

In the ERD, physical knowledge including information of physical casting process, mechanism of bleed formation, and other basic physics are fully utilized to generate the physical feature pool for bleeds. With the aid of a link module, the physical features are transferred to the pixel features applicable in the bleed detection. To overcome the difficulty in detecting irregular con-

![Fig. 4 Framework of the proposed ERD strategy](image-url)
to develop a rule-based algorithm is presented. The framework of the proposed ERD algorithm is shown in Fig. 4.

3.1 Preprocessing Using a Gray-Level Threshold. An image preprocessing is conducted to screen out the potential bleed-like contours for further identification. There are considerable background noises in the images, such as water spray, minor steam spot, and steel surface texture. A feature in gray-level is inferred based on the physical mechanism of bleed formation. Then, a group of suspicious contours can be detected using the inferred gray-level thresholds.

3.1.1 Mechanism of Bleed Formation. A "bleed" is a serious surface defect that can occur in molds with inadequate taper. The bleeds form below the meniscus due to tearing of the solid shell. The rupture of the solid shell is caused by the pulling forces exerted on the thin strand by the pinch rolls during the period when the shell is stuck to the mold. When the shell ruptures the liquid steel flows out and solidifies on the mold face as a bleed shown in Fig. 2. The physical mechanism of bleed formation is given in Fig. 5, which initially appears in Ref. [1].

The thin part of solidifying shell can be equivalently deemed as the deep oscillation mark. The depth of marks on the hot surface determines the projected gray-level in the images. The deeper the marks are, the lower the gray-levels of the corresponding contours are. When the shell ruptures and the liquid steel flows out, the rupture opening leads to a surface depression. After the liquid flows out and heals the shell, the newly solidifying bleed together with the surface depression forms a deep contour (see arrows in Fig. 5(e)). The bleed contours, together with deep oscillation marks, contribute to the darkest striae (i.e., the pixels of lowest gray-levels) in the image.

3.1.2 Feature Choice and Feature Identification. The engineering domain knowledge of casting process indicates that there are limited number of deep oscillation marks and even few bleeds on a certain area of billet surface under normal production condition. Hence, the features of preliminary suspicious contours can be concluded as follows.

(1) They correspond to the darkest contours in the image.
(2) The contours of deep oscillation marks and bleeds possess a small proportion of total pixels one image has.

Therefore, a threshold \( \gamma (\% ) \) on the number of pixels representing the lowest gray-levels is proposed to simultaneously transfer the above two physical knowledge into image features. The number of pixels is cumulated from gray-level 0 to higher level until it reaches the predesigned threshold. Mathematically, it can be expressed by

\[
\sum_{g=0}^{G} NP_g = \gamma \times TNP
\]

where \( G \) is the gray-level at which the accumulation stops, \( g \) represents the gray-level, \( g=0 \) is corresponding to the darkest gray-level in the image, \( NP_g \) represents the number of pixels of the same gray-level \( g \), and \( TNP \) represents the total number of pixels in the image. After we have \( G \), the original grayscale image is transferred into a binary image by applying the obtained gray-level threshold \( G \). If the gray value of a pixel is greater than \( G \), it will be reset to 0. On the contrary, if it is smaller than or equal to \( G \), it will be reset to 1.

The reason why we do not directly design a fixed threshold on
gray-level is that the overall gray-levels of the images vary from time to time and from image to image. It is noted that in this preliminary processing stage, the threshold $\gamma$ is the first design parameter in the ERD algorithm. The optimal selection of $\gamma$ will be discussed in Sec. 4.3.

3.2 Intermediate Processing Using the Number of Connected Pixels. Secondary screen-out processing aims to further remove the false positives (mainly deep oscillation marks) from the preliminary suspicious contour pool. Based on the estimation of geometric size of bleeds, thresholds on the number of connected pixels are determined and used as the second design parameter in the detection program.

3.2.1 Feature on Geometric Size of Bleeds. When the shell ruptures, liquid steel flows out and solidifies on the mold face. There is a heat balance between the heat transported across the air gap and the heat of solidification [12]. It is noted that the liquid metal keeps flowing out through the rupture opening until the newly solidified shell grows thick enough for pressure balance between the inner strand pressure and air gap pressure. The required minimum thickness differs from material to material and from temperature to temperature [13]. It can also be calculated through analyzing the strain and tear condition for different production environments. Physically, the shell thickness should be large enough to protect the shell from tearing. The bleed-out liquid steel keeps solidifying while it keeps flowing downwards. Eventually, a scar of solidified bleed-out liquid steel is observed on the surface of billet. Figure 6 provides an illustration of the geometric size of bleed contours.

It can be concluded based on the discussion above that $D$ is a function of various casting process variables, such as strand temperature, mold temperature, material properties, casting speed, etc. [14]. The engineering knowledge tells that for the same production batch, bleeds share a similar $D$. The three figures, Figs. 6(a)–6(c), show that the width ($L$) may vary from bleed to bleed, but the distance ($D$) is about the same for a given material and production conditions. Hence, $D$ can be reliably estimated based on sample data.

The width of bleed $L$ is dependent on the length of the rupture opening when the thin shell cracks. According to the understandings on bleed formation and the observation on sensing-images, $L$ is found varying irregularly from bleed to bleed due to the randomness of rupture openings. The estimation of $L$ distribution can be done based on sampled images. In our study, $L$ appears to follow normal distribution $N(L, \sigma_L^2)$, which is also verified by the bleeds samples. More details can be found in Sec. 4. Hence, the range of the randomly changing $L$ can be reasonably concluded as $[\hat{L}_{\min}, \hat{L}_{\max}] = [\mu_L - 3\sigma_L, \mu_L + 3\sigma_L]$.

3.2.2 Feature Transfer. The estimated physical features: $\hat{D}$, $\hat{L}_{\max}$, and $\hat{L}_{\min}$ based on sample data need to be transferred into the pixel feature—the number of connected pixels for an individual contour. The perimeter range of a bleed $P$ is estimated by

$$P_{\min} = 2 \cdot \hat{D} + \hat{L}_{\min}$$

$$P_{\max} = 2 \cdot \hat{D} + \hat{L}_{\max}$$

Based on Eq. (3), a link function $\hat{\phi} = G(P)$ is used to transfer $P$ value into the corresponding number of pixels in the image. The

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<th>Table 1 An illustrative summary on the developed rules</th>
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Fig. 7 The proposed rule-based features for crescent-shaped contours
structure and coefficients of $G(-)$ are only dependent on sensor settings, which are available from the sensor specifications. In general, a two-dimension image can be applied with the link function of the following form:

$$\psi = p \times 2 \times D + q \times L$$  (4)

where $\psi$ is the number of connected pixels, $p$ represents the number of connected pixels per millimeter in the image in the direction of $D$, and $q$ represents the number of pixels per millimeter in the image in the direction of $L$. The coefficients $p$ and $q$ are related to the sensor specifications. Then, a pair of thresholds on the number of connected pixels is determined by substituting the corresponding $D$, $L$, $\psi_{\text{min}}$, $\psi_{\text{max}}$ are determined by the optimization details are discussed in Sec. 4. Table 1 gives an illustrative interpretation on what those four rules are drawn for.

The rules selection also reflects the trade-off between miss detection and false alarm. More rules could be built for better describing the difference between a real bleed contour and a false positive, which possibly reduces the false alarm. However, keeping the irregularity of bleeds in mind, the increased rules are more easily violated so that miss detection rate will increase.

4 Case Study and Implementation in Continuous Casting Process

4.1 Image Acquisition. In this case study, the casting billets from which the sensing-images were taken come from two batches of materials: 1050 grade and 1070 grade. The billet diameter is 173 mm and its casting speed is 1 in./s; 260 sample images are collected and used in the case study. Each image is represented by a $512 \times 2048$ matrix, which consists of 1,048,576 pixels. The elements of a matrix take integer values ranging from 0 gray-level to 255 gray-level.

After inspection of pinholes in final billets and interpretation of 260 sample images by casting process engineers and quality/sensing engineers at the steel plant, 46 images are determined to contain real bleeds and named as group A, while the rest 214 images are collected and used in the case study. Each image is represented by a $512 \times 2048$ matrix, which consists of 1,048,576 pixels. The elements of a matrix take integer values ranging from 0 gray-level to 255 gray-level.

As mentioned in Sec. 3.2.1, the physical feature on the geometric size of bleeds is estimated based on sample images. The mean is 0.35, and the standard deviation is 0.05. The mean value and the standard deviation are determined by the optimization details are discussed in Sec. 4. Table 1 gives an illustrative interpretation on what those four rules are drawn for.

4.2 Geometric Size Estimation Based on Sample Images. As mentioned in Sec. 3.2.1, the physical feature on the geometric size of bleeds is estimated based on sample images. The mean
value for $D$ is used as an estimation of $D$, being $\hat{D}=3.2$ mm. The variation in $D$ is found to be ignorable. In our case, $L$ is found to follow a normal distribution with mean of 3.328 mm and standard deviation of 0.3706. An Anderson–Darling goodness-of-fit hypothesis test is used and the $p$-value equals to 0.318 that is greater than the chosen $\alpha$-level 0.10 (shown in Fig. 8), which verifies that the data follows a normal distribution [15]. Thus, we get

$$\left[\hat{L}_{\min}, \hat{L}_{\max}\right] = \left[(\mu_L - 3\sigma_L), (\mu_L + 3\sigma_L)\right] = [2.22, 4.44] \text{ (mm)}$$

### 4.3 Key Design Parameters Selection in the Algorithm

In stage 1 of the detection, the first parameter $\gamma$ in the ERD algorithm is to be optimally set. Figure 9 provides the miss detection rate and false alarm rate under different settings of $\gamma$. From Fig. 9, it can be seen that with the increase in $\gamma$, a higher false alarm rate is observed. This is because more not-so-deep marks and even steel textures are not screened out, which leads to more suspicious contours. The odds that the suspicious contours possess a similar shape feature with bleeds become larger. Besides, it is seen that at low level of $\gamma$, the miss detection rate is high but the false alarm rate is low. This is because the contour of the real bleed gets fragmentary, which brings much trouble to the progressive detections. Similarly, the false positives with fragmentary contours are more likely to be screened out in the progressive detections.

From Fig. 9, it can also be found that as Gamma is selected as 10% or larger, the miss detection tends to be stable while the false alarm rises. Considering these trade-offs, the optimal setting for $\gamma$ is selected as 10%.

In the second stage of detection, there is a link module transferring the geometric feature into its corresponding pixels feature. With the information provided in the sensor specifications, the parameters in Eq. (4) are given by $p=260, \quad q=160$. Together with $D=3.2$ mm, $[\hat{L}_{\min}, \hat{L}_{\max}] = [2.22, 4.44] \text{ (mm)}$, we get $[\hat{\psi}_{\min}, \hat{\psi}_{\max}] = [2020, 2375] \text{ (pixels)}$.

There are some inevitable uncertainties in calculating $\psi$, e.g., thermal sensor errors, nature of bleed irregularity, estimation error of $D$ due to miscellaneous minor factors, normal fluctuation of production conditions during the same batch, etc. Hence, a slight slack coefficient on threshold $\psi$ is suggested to enhance the compatibility of ERD for applications in complex and uncertain casting processes. In this case study, a slack coefficient of 10% is used, which produces $[\hat{\psi}_{\min}', \hat{\psi}_{\max}'] = [2020 \times (1-10\%), 2375 \times (1+10\%)] = [1818.2612] \text{ (pixels)}$.

On the third stage of detection, both the geometric parameters in Fig. 7 and the coefficients in the rules are to be optimized.

### Table 2 Experimental design for optimization of algorithm parameter settings

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<th>$\alpha_1$</th>
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Since \( \alpha_2 \) is related to \( \alpha_1 \) by \( \alpha_1 + \alpha_2 = 0.45 L_c \), \( \beta_2 \) is related to \( \beta_1 \) by \( \beta_1 + \beta_2 = 0.5 D \), \( k_1 = k_2 \) (refer to Fig. 7), there are four independent parameters: \( \alpha_1, \beta_1, k_1, \) and \( k_3 \). A full factorial three-level experimental design is generated for those four parameters. Applying different parameters in the algorithm, miss detections, and false alarms are collected and given in Table 2.

From Table 2, it can be found that the optimal performance of the algorithm is obtained by setting \( [\alpha_1, \beta_1, k_1, k_3] = [0.3, 0.1, 1.2, 0.25] \). The optimization objective is to simultaneously minimize miss detection and false alarm. However, extraordinary low-value of false alarm observed in Table 2 should be treated with caution. Under improper settings of algorithm parameters, none or a few suspicious contours are detected. In that case, the false alarms are apparently quite low, which could be misleading to draw a conclusion that the algorithm runs perfectly. This misperception can be avoided by looking at the miss detections and the false alarms simultaneously. Significantly large miss detections coupled with extreme few false alarms indicates a non-acceptable performance result.

In this paper, we treat the miss detection and false alarm equally important. However, sometimes people think that a missed bleed may cost significantly more than a false positive. In that case, a penalty scheme can be introduced to deal with this trade-off issue. In this case, different weighing coefficients will be applied on miss detection and false alarm, as shown in Eq. (5). A different value of \( \lambda \) leads to different optimization results (i.e., optimal settings for the proposed algorithm).

\[
PE = (1 - \lambda) \times r_{\text{miss}} + \lambda \times r_{\text{false}} \tag{5}
\]

where PE represents overall performance evaluation, \( \lambda \) is a penalty coefficient, \( r_{\text{miss}} \) and \( r_{\text{false}} \) represent miss detection rate and false alarm rate, respectively.

### 4.4 Detection Illustration and Results

Figure 10 shows how an original image is processed through the developed detection method and finally identified to contain bleeds or not. Using the optimal settings for \( \gamma, \alpha_1, \beta_i \) \( (i=1, 2) \), and \( k_j \) \( (j=1, 2, 3) \) in the proposed algorithm, the miss detection rate is 2.7% and false alarm rate is 5.7%. The performance satisfies the engineering application.

### 5 Conclusions

This paper proposed an engineering-driven rule-based detection algorithm to detect bleeds in continuous casting processes. A floating threshold on gray-level is developed to address the problem of noisy background. For the irregularity of bleed patterns, a set of rules are built to describe the crescent-shape. For the trouble from false positives, a threshold on the number of connected pixels of a contour is developed based on the estimation of geometric size of bleeds. Moreover, the parameters in the algorithm are optimized. A real case study based on real product data is presented to demonstrate the effectiveness of the proposed algorithm.

In a broad sense, the development of ERD method is a good attempt to design image processing algorithm for surface defect detection through fusion of the engineering knowledge with image processing methods. In this study, priori engineering knowledge is fully utilized to facilitate the selection of feature pools, which are traditionally obtained through machine-learning. The proposed strategy is able to work well even though the sample size is small. It should be pointed out that the quality of imaging depends on steel grade, billet size, casting speed, etc. The performance of the proposed detection algorithm is dependent on image quality. The developed algorithm has been tested in real production conditions as presented in Sec. 4.1. However, the algorithm may need to be revised when it is used for other casting products and production conditions.

### Acknowledgment

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**Fig. 10 Detection process of the proposed ERD algorithm**

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