A Multiple Background Images Model for Billet Location Control

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Abstract

This paper addresses the problem of real-time location of billet in the heating kiln of a steel mill, and presents a vision-based steel billet location control system. The locations of the billets are obtained by background subtraction method. The major difficulty is the strong illumination changes in the heating kiln with the temperature changes. This paper adopts the idea of multiple background images model to adapt the illumination changes in the heating kiln. The multiple background images model classifies the background images as three representative background images, and provides an adaptive weight mechanism for switching a background image among three representative background images. The practical experimental result shows the algorithm is effective and fast, and can meet the demand of real-time control. The vision-based location control system has been successfully used to track the billet edge in industrial condition, and can obtain good control performances under the industrial environment.

1. Introduction

In a steel rolling mill, the steel billets must be firstly heated to 1000–1200°C in a heating kiln, then are rolled into flat-blocks. With the growing demand for steel flat-blocks, the preheating process of the steel billets is becoming a crucial step to increase the yield of the steel flat-blocks. Some rolling mills have proposed a new billet range in the hearing kiln: there are two billets, not one billet along the tram road (as shown in Figure 1), which improves the processing capability of the kiln.

For the temperature in the heating kiln is over 1000°C, the plant operator cannot observe the moving of the billets in the heating kiln with the naked eye directly. Compared with other sensors developed to control the locating operation, the information provided by CCD sensors seems to be the best tradeoff between accuracy control and low cost. With a CCD industrial camera set on one side of the kiln, the plant operator can monitor the situation of billet in the heating kiln and adjust the moving of steel billets through the observation of the industrial TV (shown in Figure 2). But it is known that human operating is subjective, experience-dependent and labor intensive [10,7]. So it is necessary to realize the automation of the steel billet location.

Another problem is worth considering in the preheating of steel billet. That is, the location of billets in the kiln will deviate in the process of preheating, while the space of a kiln is limited. Thus two discrepancies must be controlled in the steel billet location: one is the discrepancy between two billets on one row, the other is the discrepancy between the billet and the wall of kiln (shown in Figure 1).

The biggest deviation permitted to assure processing is ±5cm. When the discrepancy exceeds the limit catastrophic failure, such as many steel billets stack in the heating kiln occurs which leads to a complete interruption of production and needs the operators to adjust the situation of the steel billet by hand. For this reason the automation of the billet position controlling is also essential.

In order to solve the problem, this paper has developed a fast steel billet locating system based on the visual sensor, which directly senses the billet position. In the system, a multi-images model based on background subtraction algorithm computes the billet position from the sensed billet image.
2. THE SYSTEM CONFIGURATION

The proposed steel billet locating system is a fast and low cost visual control system. A CCD industrial camera, which has been set on the heating kiln, is regarded as a visual sensor. For the CCD industrial camera has a finite viewable scene, there are two kind of sensors in the control system: one is the industrial camera which senses the moving of billet in the kiln, and the other is an impulse sensor which is arranged outside of the kiln and measures the moving of billet outside the kiln. The camera has $610 \times 170$ pixels and can acquire 25 frames per second.

The configuration of the visual control system is shown in Fig.2.

The industrial PC is a CPU with PIV 2.0GHz and 256MB memory, which is enough for the billet location control. The information of the billet location is extracted from the image data by an accurate fast location method using background images model based on the background subtraction algorithm.

3. THE METHOD

3.1 The Previous works

Background subtraction is a widely used approach for detecting and tracking moving objects in videos from a static camera. It involves calculating a reference image and subtracting each new frame from this image. The result is a binary segmentation of the image which highlights the regions of the non-stationary objects. Background subtraction is a region-based approach where the object is to identify parts of the image plane that is significantly different to the background. However, background subtraction would fail when it is confronted with a variety of real-world phenomena, such as illumination changes, shadows and inter-reflections, background object changes, and so forth.

A robust background reference model plays an important role in background subtraction algorithm. The simplest form of the reference image is a time-averaged background image. This method suffers from many problems and requires a training period absent of foreground objects. The motion of background objects after the training period and foreground objects motionless during the training period would be considered as permanent foreground objects.

Background subtraction has long been an active area of research. Many adaptive background-modeling methods have been proposed to deal with different problems. Yang and Levin [2], Cutler and Davis [3] proposed temporal averaging, median value of the pixels over a series of images; Heikkila and Silve [4] proposed to use a first-order recursive filter to integrate new incoming information to the current background model; Toyama and Krumm [5], Boult and Micheals [6] suggested more than one background model, one for long-term background and another one for short term, for increased reliability; Stauffer and Grimson[8] suggested an adaptive background mixture model, representing each pixel as a mixture of K Gaussians, and used an online approximation to update the background model; Koller et al [14] used a Kalman filter to track the changes in background illumination for every pixel; Grimson et al [15] employed an adaptive nonparametric Gaussian mixture model which can lessen the effect of small repetitive motions; Toyama and Krumm [5] address the problem of illumination changes by a frame level background maintenance mechanism, this method utilizes multiple background models, which are simply collections of pixel-level model for each pixel in the image, to rapidly adapt to the changes, as the light switch problem. The experiments prove the multiple background models can adapt well to the switching
light change. But the multiple background models suffer from slow learning at the beginning.

Although the pixel model can obtain by computing the number of foreground pixels or background pixels, the highly computing cost makes it hardly be used in the real-time control system.

There is not a fixed lighting in the kiln and the illumination in the heating kiln could change gradually with the change of temperature. Therefore, the major difficulty encountered in the billet location control is the illumination changes in the heating kiln. This paper adopts the same idea as [5] to propose a simple, fast multiple background images model.

3.2. The Multiple Background Images Model

In practice, the illumination in the heating kiln doesn’t change suddenly but gradually. The statistical approach is used to classify the background image features in the off-line learning phase. From the off-line analysis of the sensed image, this paper extracts three representative background images for the background subtraction algorithm: the high bright background \( B_1 \), the middle bright background \( B_2 \) and the low bright background \( B_3 \) (shown in Figure 3).

![Figure 3. Three background images:](image3)

(a) The high bright background image \( B_1 \)  
(b) The middle bright background image \( B_2 \)  
(c) The low bright background image \( B_3 \)

In order to adaptively distinguish the background image, this paper proposes a simple adaptive weight mechanism for switching the background image among three representative background images.

1. Choosing three 50x30 representative local areas in the sensed image to estimate the change of background image (shown in Figure 4).

![Figure 4. Three representative regions in the sensed image](image4)

2. Characteristic region extraction

In the sensed images and background images, this paper uses module matching method to compare the level of similitude of two areas. Let \( I(x,y,t) \) is the gray-scale of the current input image, \( B_{ij} \) is the gray feature of local background, \( (i = 1,2,3 , j = 1,2,3 ) \), the normalization of \( I(x,y,t) \) is

\[
F(i,j,t) = \frac{[I(x,y,t) - B_{ij}]}{[B_{ij} - A_{ij}]}
\]

where \( F(i,j,t) \) is the normalization of \( I(x,y,t) \), \( A_{ij} \) is the normalization coefficient.

Supposed the weight vector is \( K = [k_1, k_2, k_3] \), \((k_1 + k_2 + k_3 = 1 , k_i < 1)\). Then the discriminated criteria of replacement is

\[
C_i = \max_{j=1,2,3}(k_i * F(i,j,t))
\]

This paper denotes evaluation function of background images describes below:

\[
H = \max_i(C_i)
\]

3.3. Background images maintenance

In this paper a periodical updating strategy for the background images is used to speed up the image processing, where a first-order recursive filter method is used to integrate new incoming information to the current background images [4]. The background images update every M frame as:

\[
B_i(k+1) = \alpha I_i(k) + (1-\alpha)B_i(k)
\]

where \( B_i(k+1) \) is the updating background frame, \( I_i(k) \) is the incoming frame of current sensed the image, \( B_i(k) \) is the current background frame and \( \alpha \) is the updating coefficient.

3.4. Detecting the Edge of the Billet

This paper applies a novel approach to the detection of the billet edge. The concept is to determine whether the probability density of the intensity of the pixels in a particular column is significantly different from the column gray value of the background image. This is calculated in the following steps:
(1) The background subtraction intensity vector $BS(x, y)$ of the current sensed image data is:

$$BS(x, y) = |I(x, y) - B_i(x, y)| \quad \forall x$$

(5)

where $BS(x, y)$ is the intensity map of the background subtraction image, $I(x, y)$ is the intensity map of the current sensed image, $B_i(x, y)$ is the intensity map of the according background image ($i = 1, 2, 3$).

(2) The average project intensity vector $BS_c(y)$ of the column $y$ to be considered is determined:

$$BS_c(y) = \frac{1}{M} \sum_{x=1}^{M} BS(x, y)$$

(6)

where $M$ is the height of the current sensed image.

(3) This paper uses the technique of sliding window to improve the robust of algorithm. The sliding window is a 100×150 window.

If there is a moving object which brings into or removes from the sliding window, the column intensity and the intensity different between two columns will change [7]. Therefore, this paper uses the intensity difference between two columns in the sliding window and the change of column average intensity as the feature of the moving billet. The feature of the billet edge can be described as a vector $T$:

$$T = [T_1, T_2]$$

(7)

where $T_1$ is the number of the project intensity change columns, $T_2$ is the number of the intensity change between different columns.

The number of project intensity change column is:

$$BS_c(y) > Th_1 \Rightarrow T_1 = T_1 + 1$$

(8)

The number of project intensity change between different columns is

$$|BS_c(y) - BS_c(y + n)| > Th_2 \Rightarrow T_2 = T_2 + 1$$

(9)

where $n$ is the column interval(n<150), $Th_i$ is the change threshold of the project intensity change column, $Th_2$ is the change threshold of the project intensity change between different columns.

(4) Detecting the edge of the billet

According to the theory of nearest neighbor decision, the discriminated function is:

$$\|T - A\| = \sqrt{(T_1 - a_1) - (T_2 - a_2)} < Th_3$$

(10)

where $Th_3$ is the threshold of the feature distinction, $A = [a_1, a_2]$ is the feature template of the billet edge on the sliding window, $a_1$ is the number of intensity change column on the feature template, $a_2$ is the number of intensity change between different column on the feature template.

3.5. The Control Strategy

For the billet is about 1800 kg, the inertia of billets makes the billet sliding on the tram road when the stepper motor has stopped. This paper adopts a two stage control strategy to solve the sliding problem of the billets.

The stepper motor controller is a PLC control system where PID control algorithm is adopted. So the vision-based control strategy includes two stages: firstly, the billet is rapidly located at some certain position in the kiln, then the billet is precisely located on the expected position by PID feedback control. Figure 5 shows the final location of two billets.

Figure 5. The final precise location of one billet

Figure 6. The final precise location of two billets

4. EXPERIMENTAL RESULTS AND DISCUSSION

The algorithms were tested on a kiln in a factory workshop of a steel milling which is 27.9m in length and 12.9m in width. The image sequences were acquired in real-time at the rolling mill.

Based on this recognition algorithm and combined with the PID algorithm, the vision-based location control system drives the stepping motor to adjust the situation of the billet. The algorithm produces stable results under the industrial environment.

To evaluate the robust, accurate control capabilities of the visual location control system in the difference operation conditions, this paper made 4086 real-time billet locating operations with difference lighting conditions and background images. The results are shown in Figure 7. Some control results are illustrated in Figure 5 and Figure 6.
The result of this algorithm is presented in Figure 5 and Figure 6. These have been chosen since they represent one billet location and two billets location respectively. In Figure 5 two billets are accurately controlled at the low bright background. In Figure 6 one billet is accurately controlled at the high bright background.

![Figure 7. The statistical number of the average deviation, and the location deviation Δ ≤ ±5cm](image)

The algorithm is able to locate billets accurately, with an averaging success rate of 97.94% under the industrial conditions, much higher than the human operating system whose success rate is about 76% at the average ±5cm location deviation.

The system uses the obtained location deviation to drive the stepping motor to adjust the position of the steel billet. The experimental result showed that in the image period from image capturing to output the average deviation could reach to 40 ms when the CCD camera worked in PLC state.

This paper sets the period to 50 ms forcedly using an accurate timer in the program in order to obtain accurate control of the system so the system can process 20 frames in one second.

But the system may still make mistakes because of complex and poor environments, e.g. the very strong lighting in the kiln, or the full black in the kiln. So an operator is still needed to monitor the control system. If some incredible result occurs, the program will send a message on the computer screen to alarm the operator to adjust the billet manually.

If the environment in factory is stable, the control system can always reach a below 1% false alarm rate. To improve the performance of the visual location control system, future research will be devoted to finding more and better features in the background image and better algorithms.

5. CONCLUSION

A vision locating system is established which can use under harsh industrial conditions, and sense the moving of the steel billets in a frame from the front of the kiln. The practical experimental result shows the algorithm is effective and fast, and can meet the requirement of real-time control.

Statistical techniques have been used during image processing to detect the edge of the billets. The use of statistical techniques is a key issue for the implementation of locating billet in such environments. Experimental results showed that the algorithm is effective and fast. The period of image processing can reach 40 ms.

This vision-based location control system has been successfully used to track the billet edge in industrial condition. It adapts to the slow illumination changes in the heating kiln, but may be making mistakes for very poor operate environment. Therefore, the performance and reliability of the locating system still needs improvement.

6. References


