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Iron Ore Green Pellet Diameter Measurement by Using of Image Processing Techniques

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Abstract: Automatic Quality control is a vital process in many manufacturing process such as steel industry. Pellet size monitoring and control is a critical process which is done in steel making to improve quality of products. According to the technical reports, pellet size should be fall in the range of 9-16 mm in diameter. Larger or smaller pellets could degrade the final products and impose extra overheads to industry. In this paper, a new method is proposed for measuring the pellet size using practical Image Processing algorithms. In this method, active contour with Chen-Vese method is used to eliminate the images backgrounds and achieving a distinguishable plot of the objects. After detecting distinct elements existing in the image, the number of pellets in each object is determined and each object is classified as singular, double, triple or more pellets using an SVM classifier. Finally, morphological methods are used to estimate the real size of pellets and the pellets size histogram is presented. This practical method was applied in Mobarakeh Steel Complex, where the method was tested on about 1000 prototypes. Results showed that we have 95.1% of accuracy for detection of one pellet elements and in classification by SVM 95.6% of elements were classified correctly.

Keywords: Active contour, Pellet, Morphology, SVM.

1. Introduction

Iron Ore Mining Companies often further refine the extracted ore to produce iron ore pellets which have a uniformly high grade of iron oxide. Green pellets are produced primarily from crushed iron ore in a rotating pelletizing disk and then are baked in a furnace to produce hardened black pellets. Iron ore pellets are particularly useful for steel manufacturers as they provide a consistent and high quality iron input to the furnace [6]. Variations in pellet size distributions have negative effects on the baking process as well as product quality. These effects can be reduced by continuously monitoring the pellets size and improving the pelletizing disk process. There are a little works in the literature regarding the pellet size estimation through image processing techniques. Masami Harayama and Mitsuki Uesugi use Power Spectrum of the Pellets Image to estimate the diameter of the pellets [5]. In their work, \( f(x,y) \) represents Image in x and y directions and power spectrum is defined as:

\[
P(u, v) = \left| \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) e^{-2\pi j (ux + vy)} dx dy \right|^2
\]  

(1)

Enlarged image of \( f(x, y) \) by “a” times in both x and y directions would be \( f\left(\frac{x}{a}, \frac{y}{a}\right) \) and the Power Spectrum changes to:

\[
P'(u, v) = \left| a^2 \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) e^{-2\pi j (au x + av y)} dx dy \right|^2
\]
\[ a^4 P(au, av) \]  \hspace{1cm} (2)

By defining Image Moment \( M_n \) as:
\[ M_n = \int_0^\infty U^a P(u, o) du \]  \hspace{1cm} (3)

For the image \( f(\frac{y}{a}, \frac{x}{a}) \) could say:
\[ M'_n = \int_0^\infty U^a a^3 P(au, o) du = a^{3-n} M_n \]  \hspace{1cm} (4)

So:
\[ \frac{k M_n}{\sqrt{M_{n+k}}} = a \times \frac{k M'_n}{\sqrt{M'_{n+k}}} \]  \hspace{1cm} (5)

Therefore, if the average pellets size in one image would be ‘a’ times bigger than the other image, the ratio of their \( k \) root of Moment will be ‘a’ as well.

In this method the average pellet size is determined without any information about each individual pellet size separately.

Matthew J. Thurley and Tobias Andersson use of a 3d method to estimate the size of pellets [6]. This 3-D method is based on taking 4000 images per second by Laser and a special camera. Captured images are used to generate a 3-D surface. Different edge detection algorithms have been used to extract edges and the pellet diameter is estimated consequently.

To analyze the pellet sizes, this method is based on capturing images from the pellets on the conveyer. In some factories, different pelletizing disks have the duty to feed one conveyer. It means products of different disks cannot be distinguished. Thus, this method does not lead to recognition of malfunctioning disk. Moreover, very high rate image capturing also tends to cause severe problems and make its implementation difficult in real-time.

2. Background Omitting

In the first step of the algorithm, the background is detected and then omitted from the image. In this step, accuracy and precision play an important role. After omitting of the background, all elements are assumed to be pellets. The method mostly used for this purpose is color data method. Along this method, the background color is distinguished and then a threshold is defined. Pixels having less brightness comparing to the threshold are assumed as background and others are considered as elements. Nevertheless, environmental light variation and existence of extra spots on the background plane lower the practicality of this method. This point also should be added that the boundaries extracted in this method are not exactly placed. For these reasons, it is tried to introduce a more efficient method.

2.1 Active Contour Model

Active contours can be divided into two classes; edge-based contours and area-based contours. Classic active contours are based on edges. It means the condition on which the contour is stopped, depends on the image edge gradient. On the other hand, area-based contours are not dependant on the image gradient and rely to image segmentation Instead.

The most important advantage of the area-based contours is simple detection of objects with no exact boundary gradient. For example, objects with a uniform and smooth boundary or non continuous ones can be easily detected by this model. This is while other models depending on edges, can only detect images with exact boundary gradients. After all, it seems active area-based contours can be more efficiently utilized.

![Fig. 1: The result of object detection. First row is for Chan-Vese, second row is for classic methods.][1]

Active area-based contours were first proposed by Chan and Vese in 1999 and 2001[8]. In that record, a new model was introduced, named as Chan-Vese Model for active contours. This model can sufficiently detect objects in any image, especially images not having exact limiting edges.

In this model, the limiting condition can be defined from Mumford-Shah [9] segmentation technique. Remarking its efficiency, this model can simply detect objects having no limiting edge gradient and has much easier implementation due to its structure. The location of the starting contour is free to be set on any point of the image, which shows the most significant advantage of this model.

2.1.1 Chan-Vese Model

Considering the image \( u_0(x, y) \), the minimized energy function can be defined as:
\[ F(C) = F_1(C) + F_2(C) = \lambda_1 \int_{\text{inside}(c)} |u_0(x, y) - c_1|^2 dxdy + \lambda_2 \int_{\text{outside}(c)} |u_0(x, y) - c_2|^2 dxdy \]  \hspace{1cm} (6)
Where $C$ refers to the considered contour. $C_1$ and $C_2$ are defined as the average light intensity of the image $u_0$ in inside and outside of the contour respectively. According to this equation, if the contour $C$ is placed inside the object, then:

$$F_1(C) \approx 0 \quad \& \quad F_2(C) > 0$$  \hspace{1cm} (7)

Fig. 2 shows all the situations of $C$.

By adding some parameters such as the length of the contour $C$ and the covered area, the function …… can be completed as:

$$F(C) = \mu \cdot {\text{Length}}(C) + v \cdot \text{Area}(\text{inside}(C))$$

$$+ \lambda_1 \int_{\text{inside}(C)} |u_0(x,y) - c_1|^2 \, dx \, dy$$

$$+ \lambda_2 \int_{\text{outside}(C)} |u_0(x,y) - c_2|^2 \, dx \, dy$$  \hspace{1cm} (8)

$\mu$, $v$, $\lambda_1$, and $\lambda_2$ are positive constants. $\lambda_1$ and $\lambda_2$ are used to adjust the object detector sensitivity. Also to filter the high frequency noises in the model, the value of $\mu$ should be taken as high as allowed. Comparing to that, $\lambda_1$ and $\lambda_2$ should be taken as low as possible simultaneously. On the other hand, if the purpose is to detect objects with details, the value of $\mu$ should increase and $\lambda_1$ and $\lambda_2$ should decrease.

It is totally implied that setting these parameters correctly can lead to the best result achievement.

Fig. 3 shows the result of 6000 iteration of Chan-Vese algorithm.

Comparing the results attained from the threshold method to Chan-Vese model, it can be implied that less unsuitable elements are recognized in the second one. Also the boundaries detected in Chan-Vese are more realistic and exactly placed. The only disadvantage of the contour method is slower processing speed than the threshold method.

### 3. Pellets Quantity Determination

Using a 3 Mega-Pixel network camera and getting supplementary data from pelletizing section of Mobarakeh Steel Complex, A database was prepared. This database included 200 images as samples, taken in different conditions and each image included many elements. It was observed that about 46% of the recognized elements included one pellet, about 18% included two, 7% included three and the rest of the element included more than three pellets. In this Statistic Population pellets have random and independent movements and there exists no gravity between them thus this Statistic Population can be assumed a suitable one. Considering the distribution rate of the elements with less than four pellets which of course play a dominate role is the Statistic Population, it seems that they can be processed as the main data needed to pursue the proposed algorithm.

#### 3.1 Single-Pellet Elements

It can be assumed that the shape of the single pellet elements is close to a circle. The fact that the whole pellet is the same as a sphere also emphasizes this. This is not true about other elements because of the overlapping in such ones.

The following criterion is proposed to determine the circularity of an element:

$$\text{metric} = \frac{4 \cdot \pi \cdot \text{area}}{\text{perimeter}^2}$$  \hspace{1cm} (9)

The following criterion is simplified for a circle shape to:

$$\frac{4 \cdot \pi \cdot (\pi \cdot r)^2}{(2\pi \cdot r)^2} = 1$$  \hspace{1cm} (10)

Simply, the result of this criterion is calculated for all elements and if it is more than 0.8, the element is categorized as simple-pellet element.
3.2 Two-Pellet and Three-Pellet Elements

After recognizing one-pellet elements and omitting them from the sample space, six parameters are introduced to analyze more-than-one-pellet elements. A Support Vector Machine classifier analyzes the parameters and determines the number of pellets existing in an element. These six parameters include:

3.2.1 Number of the Peaks in the 3-D Image

A 3-D image can be defined as a 2-D image including x and y vectors, and then light intensity is added to it as the third dimension. There show up many ups and downs in this 3-D model which are all resultants of light non uniform distribution and pellets unsmooth outer surface. It also has to be mentioned that often the center of a pellet has more light reflection (Fig. 4).

To eliminate extra un-smoothness of the plot, a Gaussian filter with a window size of 15*15 and sigma of 4.5 is imposed to the elements. Although this filter does not have a maximal flat and leads to image blurriness which of course is ill favored, it has a considerably positive effect in the proposed method.

3.2.2 Summation of Image Pixels in the Same Column After the Rotation of Element

At the beginning, the smallest surrounding ellipse of the element is found (Fig. 5).

Then the angle between the main axis of ellipse and the horizontal axis is estimated. Next, the element is rotated equal to this angle to get parallel to the horizontal axis. The columns of the image are added together and the resulting graph is drawn. It is seen from this graph that the curve has different ups and downs. If an element consists of two pellets, the graph will have two peaks. Generalizing that, an element with ‘n’ pellets linearly, will have ‘n’ peaks in the graph as well (Fig. 6).

in order to eliminate the effects of noises in the graph, a FIR Butterworth filter is used. The parameters of the mentioned filter are illustrated in Fig. 7:FIR filter
3.2.3  Perimeter and Area
As it is obvious, the more the number of pellets, the more the value of area and perimeter. So these two parameters can also be considered as a feature of an element.

3.2.4  Width of the Surrounding Rectangular of the Rotated Element And its Length to Width Ratio
After rotating the element, these two parameters can be useful if an element contains pellets positioned linearly.

3.3  Support Vector Machine
After defining the previous six features and by the usage of a Supporting Vector Machine, now the number of the pellets in an element could be estimated. Among the functions used as kernel in the Support Vector Machine, the Gaussian function with $\sigma = 1.3$ leads to best results.

4.  Diameter Estimation
Based on the number of containing pellets, the area of the elements with one pellet can be estimated by adding the number of white pixels together. Then the diameter can be calculated from the estimated area.
For elements containing two pellets, the algorithm of diameter estimation is a little different. In this case, morphological methods can be beneficial. This algorithm starts by erosion. The structure element considered for erosion is defined as a disk. Since a disk can be approximated to a polygon, the method can be considered as a Logarithmic Decomposition [2]. The methods utilizing disks as structure elements are based on a technique named as Radial Decomposition Using Periodic Lines [3,4].
In the first step, the diameter of the disk is presumed as 1. In each step, the diameter is increased until the under processing element, which of course contains two over-lapped pellets, is partitioned into two pieces. These two partitions are dilated with the same disk as before individually. This algorithm leads to two separate pellets of which the diameter can be calculated by the process explained for one pellet element before.
For elements containing three pellets positioned linearly the algorithm goes on similarly.

Conclusion
In background omitting using Active Contour, 99.1% of pixels were classified correctly. While by using threshold method only 97.3% of pixels were done so. Meanwhile, we can reach to 95.1% of accuracy for detection of one pellet elements as real positive. In classification by SVM 95.6% of elements were classified correctly. Also the morphological method has more than 90.3% of accuracy in diameter estimation.

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