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Image Processing Based Defect Detection and Recognition of Embossed Characters in Induration Conveyor for Pellet Plant

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Abstract: Pellet plant is a crucial entity in an integrated steel plant. It producespellets from fine-grained iron ore. These pellets form the basis of raw material fed into blast furnace to produce steel. The quality of pellets in terms of its chemical and physical composition affects the chemistry of steel produced. Hence it is imperative to control the process of pelletizing. Palletization is achieved using heat treatment of raw pellets moving over a special induration conveyor. The conveyor consists ofcars, wherein each car has grate structure over which a bed of pellets is stacked for heating.Due to continuous thermal and mechanical stress, the grate bars deform and eventually break off giving rise to a defective car. A defective car caused thermal instability in the process and leads to degraded quality of pellets. Also, each car has a unique number embossed on it. This helps to track the defective car along the conveyor and perform maintenance operation on it. Traditionally, a manual procedure of checking the cars for defects is performed in plant based on a time schedule.

We have developed an image processing based system which can identify and quantify dislodged grate bars, track defective car and provide a predictionof its lifetime with replacement notification. It consists of industrial machine vision camera andcustom lighting.

This paper presents a methodology for detecting the defective carusing image processing based defect detection algorithm. Also, we present a method to identify and recognize the embossed car number using a custom light setup and image processing techniques. These methods are suitable to find defects in grate bar based induration conveyors operating in other industries such as coffee production and sinter plant.

Keywords: Induration conveyor, grate bar defects, embossed number, image processing.

1. Introduction

In steel industry, molten steel, also known as hot metal, is produced from iron ore in a blast furnace. Iron ore pellets, among others, are the most important raw material fed into the blast furnace. The qualityof steel produced is influenced by the grade of pellet used. High quality hot metal is obtained by controlling several process parameters within the blast furnace which in turn depends on superior grade of raw material. Any deviation from the specified composition of pellet will lead to degradation in the quality of produced hot metal and affect the critical operations of blast furnace.

In an integrated steel plant, the task of providing high grade pellets resides with the pellet plant wherein finely ground iron ore concentrates are converted into small pellets, called as green balls, having diameter of 10-20mm. The pelletizing process is currently the most widely used method for producing suitable raw materials for iron making from fines of iron ore concentrates. Pellets provide advantage to blast furnace to improve its productivity by increasing the iron content of the charged material. The pelletizing process consists of three steps:

1. Feed preparation and mixing: Raw materials such as iron ore concentrates, additives and binders of required particle size and chemical composition are mixed together.
2. Balling process: Green pellets are formed in circular disks under strict control of moisture and rotation speed to obtain small spheres.
3. Induration process: The green pellets are hardened under a high temperature furnace at controlled heating rates to achieve the required physical and metallurgical properties for handling, transportation and feed the blast furnace.

The quality of green balls depends on the mineral composition, granularity of ore fines and process parameters such as feed particle size, amount of water used for agglomeration of fines, disc rotating speed and inclination of disc [1] [2]. The resultant green balls are wet and fragile. It needs to be hardened for ease of handling and transportation. This is performed in an induration conveyor with heat treatment. An induration conveyor consists of drying, oxidation, sintering and cooling zones. Green balls pass through this continuous conveyor to solidify and strengthen. A typical induration conveyor consists of cars which are interlinked to form a continuous bed over which the pellets travel.A layer of indurated pellets is arranged at the bottom of each car to protect it against the heat [3]. A schematic of an induration conveyor is shown in **Figure 1**. The induration conveyor is a 200-meter-long conveyor consisting of 282 sections, each called as a car. From one side, green balls are fed into it which passes through the furnace to harden and are collected at the other end.

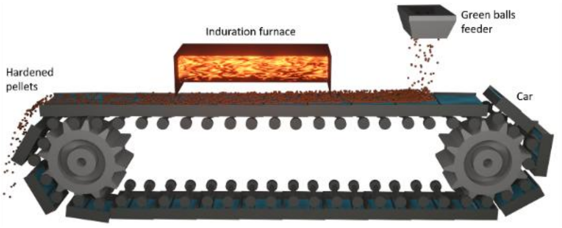

Figure 1: Schematic of an induration furnace

Each car has several grates like structure placed adjacent to each other with a gap of 6 mm. This gap ensures the uniform heating and cooling of pellets. Grate bars are subject tohigh stress from thermal load due to high temperature variation between the heating in furnace and cooling down in ambient air in every cycle. As time passes, grate bars start to dislodge causing the gap to widen significantly (>40mm). Moreover, dislodging of one grate bar create a domino effect and accelerates deterioration of others.

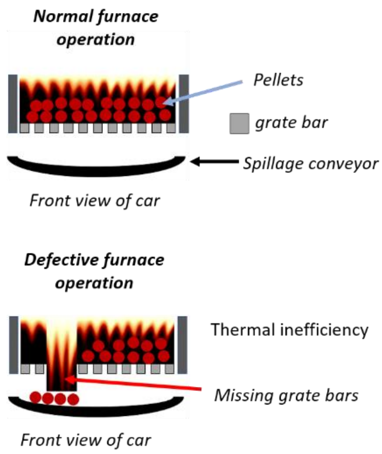

Figure 2: Thermal inefficiency caused by missing grate bars

The gap created by the missing grate bars allow pellets to fall through them and further cause thermal fluctuation due to escaping heat thus deteriorating the process control parameters as shown in **Figure 2**.**Figure 3**shows the layout of grate bars on a single car. A defective grate bar is also visible in the figure.

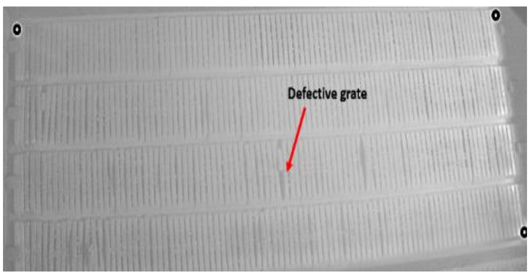

Figure 3: layout of grate bars in a car

Once a grate bar has been damaged, it deteriorates the car utilization progressively with time. The defects occurring can be classified into stages based on the severity and the width of the gap due to missing grate. Defect stages 4 and 5 can lead to severe underperformance of critical aspects of the process. **Table 1**shows the sample images of each defect stage along with its occurrence frequency and impact on the process control parameters.

Defect sample			
Stage	1	2	3
Event	Happen at anytime	Few weeks after stage 1	Few days after stage 2
Impact	The adjacent grate bars are continuously overheated until it cracks and falls off.	Quicker degeneration of grate bars. Process disturbances are already noticeable.	Entire row of grate bars falls off. This will lead to major process disturbance and premature equipment failure.

Table 1: Stages of defect in grate bars

Each car in the conveyor has a unique number embossed on it. The cars travel through an induration furnace where the surface of the car is subjected to temperatures of over 1000 degree Celsius [3]. Anumber written in standard paint cannot withstand such temperatures, hence the number is embossed on the car body during its casting.

Figure 4: Embossed car number

Figure 4shows an example of a car number.This number helps the operators to identify the defective car and to track its location in the conveyor. Once the car reaches near the maintenance bay, the conveyor is stopped to replace the damaged car.

This paper first describes the system design undertaken to develop a vision acquisition system comprising of camera and lighting for capturing images of the conveyor cars. This is followed by an explanation of the defect detection algorithm developed to detect the broken grate in conveyor using custom image processing. Finally, we propose a template matching based methodology to recognize the car number required for tracking the defective car in the conveyor.

2. System design and description

The image processing methods proposed in this paper for defect detection and embossed character recognition utilizes images captured from the machine vision system designed and developed to acquire images of the conveyor cars in the harsh environment of plant operations. The system essentially consists of a pair of industrial machine vision camera of high resolution and optimum frames per second required to capture images of the moving conveyor with minimum blurring caused by motion. Also, compactible lens is used to focus each camera on an entity of the conveyor viz. the grate bars and the embossed number. Each camera is housed in an air-cooled enclosure to ensure the electronics are functioning under an ambient temperature range and avoid exposure to the high temperature near the conveyor. Also, the enclosure protects the sensitive optical devices from accumulation of dust.

A custom lighting setup is created wherein a source of LED light is installed near the conveyor at an angle to the direction of movement of car to create a directional lighting. This type of illumination ensures that a shadow is cast by the embossed numbers. The shadows are detected to recognize the car number. A laser distance meter is used to sense the position of the car to generate trigger for the image acquisition system. For each car, two images need to be acquired at different positions during its movement. The first image is captured when the complete face of the car is visible to first camera to obtain an image in which all the grate bars of the current car are seen.

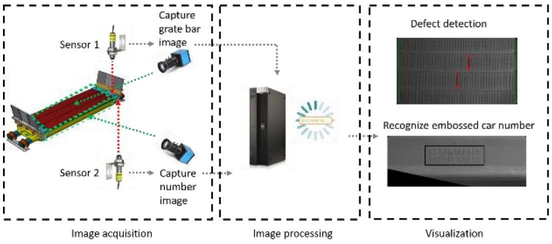

Figure 5: Schematic of the machine vision system

The second image is captured when the car number is visible to second camera. A data acquisition card captures the trigger signal to initiate image acquisition. Once the images are captured, they are processed in a workstation which runs the image processing algorithms to analyze the first image for defect detection and second image to read the embossed car number. **Figure 5** shows the schematic of the machine vision system and data flow.

3. Grate bar defect detection

Machine vision systems are often used in industrial applications to detect, monitor and control critical processes. These systems perform nondestructive analysis using a camera without requiring sophisticated control systems to increase productivity and efficiency of a process. It can assist in performing simple tasks at high speed such as counting of objects and check for presence or absence of critical parts. Current state of the art computing hardware and GPU driven optimization in image processing algorithms ensures much more sophisticated tasks such as defect detection, number recognition and optical flow are calculated in real time.One of the most frequent use of a machine vision system is to find defects in a manufacturing line, especially one running at high speed. Even a trained human can make an error in judgement in these high-speed scenarios. Machine visions systems are an ideal solution in such cases where continuous monitoring of process is required with high precision and repeatability.

This section describes the image processing algorithm developed to identify the defective grate bars present in the car image.We first mention the preprocessing steps required to correct the image for perspective distortion caused by the camera. This is followed by a comparison of thresholding methods to decide the best suited for our application. Finally, we describe a methodology to detect the defects in grate bar based on the width of the gap between the grates.

3.1 Preprocessing

It is observed from the image acquired by the first camera that the plane of the image sensor is at an angle to the plane of the face of the car. This causes the car to appear tilted in the image. Due to space restriction on field, the camera is place with a slight skew with respect to the plane of the car giving rise to the deformity. The first step in the algorithm is to correct for the tilt in image. This is performed by computing a4-point perspective transformation to correct for the change in perspective. The perspective transformation is expressed as **Equation 1**.

$$\begin{bmatrix} t_i X' \\ t_i Y' \\ t_i \end{bmatrix} = \begin{bmatrix} a_1 & a_2 & b_1 \\ a_3 & a_4 & b_2 \\ c_1 & c_2 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} \#(1)$$

where $\begin{bmatrix} t_i X' \\ t_i Y' \\ t_i \end{bmatrix}$ is the scaling factor and $\begin{bmatrix} a_1 & a_2 & b_1 \\ a_3 & a_4 & b_2 \\ c_1 & c_2 & 1 \end{bmatrix}$ is

the transformation matrix. Here (X', Y') are the transformed points and (X, Y) are the input points. The transformation matrix is defined by 8 constants so to find these we first select 4 points in the input image and map them to the desired location in the output image.

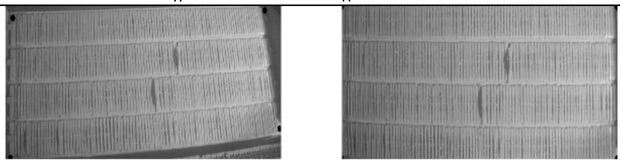
(a) (b)

Figure 6: Transformation matrix result (a) Original image (b) Perspective corrected image

Once the transformation matrix is calculated, we apply it to obtain the final transformed image. This transformation is shown in **Figure 6**.

We have now obtained an image which is corrected for perspective distortion. The image is manipulated using the perspective transformation such that it appears as if the camera sensor plane and the object plane are parallel to each other. We now must find the defective grates present in the image. Ideally, we must obtain a binary image wherein the defective regions are separated from the non-defective regions.For this we must perform a thresholding operation onto the image. There are several methodologies to perform a threshold viz. global, adaptive and Otsu's method. We shall first compare the results of each thresholding method to select the best performing method in our situation. Thresholding is a type of image segmentation where we change the pixels of an image to make it easier for further processing such as object and defect detection. In thresholding, we convert a color or grayscale image into a binary image such that the objects of our interest are represented by white and all other background regions are denoted by black. Most frequently, we use thresholding to select areas of interest in an image [4]. There are several ways to achieve this. We shall compare 3 methodologies:

1. Global thresholding: It is used when the intensity distribution between the objects in foreground and background are distinct. In such a case, a single value of threshold can be used to easily differentiate between the foreground and background regions. Thus, in this type of thresholding, the value of threshold T depends on the pixel intensity and gray value distribution of the image. The pixels are separated based on **Equation 2**.

$$g(x,y) = \begin{cases} 1, if\ f(x,y) > T \\ 0, if\ f(x,y)\ \leq T \end{cases} \#(2)$$

where $f(x,y)$ is the input image, $g(x,y)$ is the output image, T is the global threshold value and (x,y) are the pixel location.

2. Otsu's method: To make segmentation robust, the threshold value should be automatically calculated based on the image. One such method is Otsu's [5]. It measures the homogeneity of a region by calculating its variance, a region with high homogeneity will have low variance. It is widely used in pattern recognition, document binarization and computer vision. In many cases, Otsu's method is used as a pre-processing technique to segment an image for further processing such as feature analysis. It searches for a threshold that minimizes the intra-class variances of the segmented image and can achieve good results when the histogram of the original image has two distinct peaks one belonging to the background and the other for foreground. Such a histogram is called a bi-modal histogram.**Figure 7** shows a typical bi-modal histogram distribution.

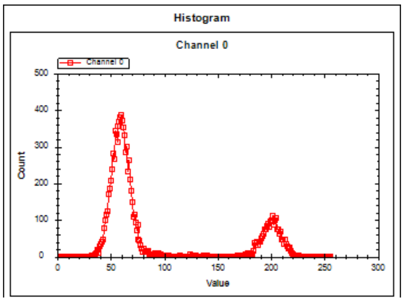

Figure 7: A bi-modal histogram

The threshold value is found by searching across the whole range of pixel values [0,255] of the image until the intra-class variances reach their minimum. The weighted within-class variance is given by **Equation 3**.

$$\sigma_w^2(t) = q_1(t)\sigma_1^2(t) + \ q_2(t)\sigma_2^2(t)\#(3)$$

where the class probabilities are estimated as **Equation 4 & 5**.

$$q_1(t) = \sum_{i=1}^{t} P(i) \#(4)$$

$$q_2(t) = \sum_{i=t+1}^{I} P(i) \#(5)$$

and the class means are given by **Equation 6 & 7**.

$$\mu_1(t) = \sum_{i=1}^{t} \frac{iP(i)}{q_1(t)} \#(6)$$

$$\mu_2(t) = \sum_{i=t+1}^{I} \frac{iP(i)}{q_2(t)} \#(7)$$

And the individual class variances are given by **Equation 8 & 9**.

$$\sigma_1^2(t) = \sum_{i=1}^{t} [i - \mu_1(t)]^2 \frac{P(i)}{q_1(t)} \#(8)$$

$$\sigma_2^2(t) = \sum_{i=t+1}^{I} [i - \mu_2(t)]^2 \frac{P(i)}{q_2(t)} \#(9)$$

We now iterate over the full range of t values [0,255] and pick the value of t that minimizes $\sigma_w^2(t)$. One of the drawbacks of Otsu's method is that it may create suboptimal results when the histogram of the image has more than two peaks or if one of the class has a larger variance. Further the method does not work well with variable illumination.

3. Local adaptive thresholding: In local adaptive technique, a threshold is computed for each pixel based on local statistics such as mean, standard deviation or variance of the neighborhood pixels. Mathematically, it can be expressed as**Equation 10**.

$$g(x,y) = \begin{cases} 0, & if\ I(x,y) \le T(x,y) \\ 1, & otherwise \end{cases} \#(10)$$

where $g(x,y)$ is the resultant binary image and $I(x,y)$ is the intensity of a pixel at location (x,y). $T(x,y)$ can be calculated by using **Equation 11**.

$$T(x,y) = \mu(x,y) + k * \delta(x,y) \#(11)$$

where $\mu(x,y)$ and $\delta(x,y)$ are the local mean and standard deviation of the pixels inside the local window of size (w,w) and k is a bias factor [6]. This is popularly called as Niblack's technique [7]. The local mean and standard deviation calculated adjusts the value of threshold according to the contrast in the pixels within the window.

Another local adaptive thresholding which uses mean and standard deviation to compute the threshold is Sauvola's technique [8]. The threshold $T(x,y)$ is computed using the mean $\mu(x,y)$ and standard deviation $\delta(x,y)$ of the pixel intensities in a window of size (w,w) centered around the pixel at (x,y) and expressed as **Equation 12**.

$$T_{Sauvola} = \mu * \left(1 - k * \left(1 - \frac{s}{R}\right)\right) \#(12)$$

where R is the maximum value of the standard deviation (i.e. 128) and k is a parameter which takes value in the range [0.2, 0.5]. The parameter k controls the value of the threshold in the local window so that the higher the value of k, the lower the threshold from the local mean.

A third type of local adaptive threshold uses local gray range. In this technique, the range between the maximum and minimum pixel intensities within the local window is used to find the threshold value. The threshold value $T(x, y)$ at (x, y) is calculated within a window of size (w, w) using the **Equation 13**.

$$T(x, y) = 0.5\left(I_{\max\,(i,j)} + I_{\min\,(i,j)}\right)\#(13)$$

where $I_{\max\,(i,j)}$ and $I_{\min\,(i,j)}$ are maximum and minimum gray intensity within the local window provided the contrast satisfies **Equation 14**.

$$C(i, j) = I_{\max\,(i,j)} - I_{\min\,(i,j)} \geq 45\#(14)$$

The threshold is set to the mean of the maximum and minimum gray intensities in the window. If the contrast is below a certain threshold, then the neighborhood is said to consist of either foreground or background. There is no bias factor to control the effect of the threshold value. This method is called Bernsen's technique. We now compute the above three methods of thresholding in our case and compare the results. **Figure 8** shows the result of performing global thresholding,Otsu's method and local adaptive thresholding on a grate bars image.

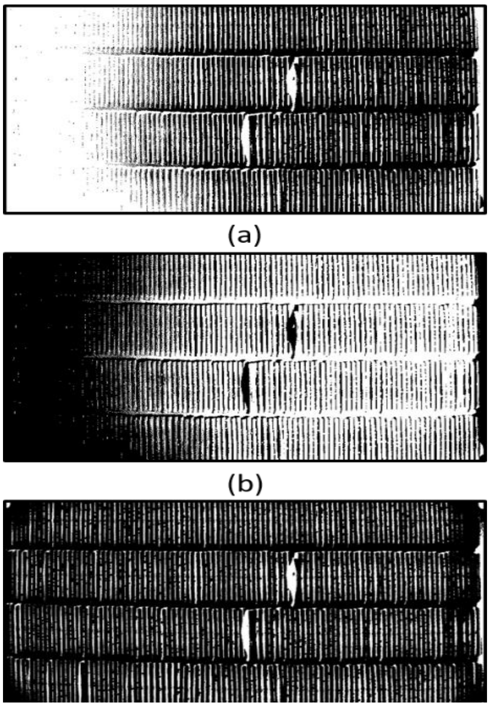

Figure 8: Comparison of thresholding techniques (a)global (b)Otsu's and (c)local adaptive threshold

It is observed that both global threshold and Otsu's method gives very poor segmentation result. In global thresholding, a section of the image is over segmented and in Otsu's method a section of the image is under segmented. However, in case of local adaptive thresholding, we obtain an optimal segmentation throughout most of the image except for extreme ends where the contrast drops significantly for even adaptive threshold to work.

The reason for the failure of the two methods can be root caused to the uneven distribution of light across the image owing to a large field of view of the camera (~3 meter across).

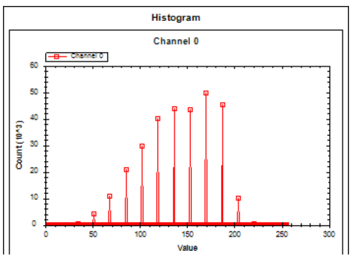

Figure 9: Histogram of original grate bars image

This is verified from the histogram of the original image as seen in **Figure 9**. There are multiple peaks seen in the histogram due to variation in the illumination. A local adaptive thresholding is best suited for this situation.

3.2 Algorithm and result

The width of gap between the grate bars is the ideal parameter to detect whether a grate is missing from a location giving rise to a defect. The next step is to perform a segmentation which would yield us the gaps between the grate bars. From the captured image, it is observed that the gaps between the grate bars appear to have lower pixel intensity when compared to the surface of the grates. This is because light can reflect from the surface of the grate bars into the camera whereas the depression between the grates receive lesser amount of incident directional light. There is fluctuation in the illumination across the field of view due to large width of the car (~3 meters). A global thresholding approach will not yield good result due to this variation in intensity. Hence, we apply a local adaptive thresholding technique using a suitable kernel. In this method, the algorithm determines the threshold value based on the local pixel intensities within the said kernel. So, different threshold values are calculated for different regions of the image. The adaptive method employed by us uses the mean of the neighborhood pixels within the specified kernel size as the threshold value. The segmentation result is shown in **Figure 7 (c)**.

Once segmentation is performed, we have obtained a binary image which isolates the gaps present between the grate bars from the grate. To obtain the defective regions in the image, we first compute the width of each gap(W_i) and pass the resultant array through a particle filter. The particle filter sets a constraint on the variable (W_i) such that region (R_i) having a (W_i)> T, where T is the threshold, corresponds to a missing grate bar(s). This is expressed as **Equation 15**.

$$R_i = \begin{cases} 0, & W_i < T \\ 1, & W_i \geq T \end{cases} \#(15)$$

Where

$$\mathrm{T} = \text{Width of grate bar in pixels}\#(16)$$

Here T can be calculated using**Equation 16**. Based on the computed value of T, we obtain a set of regions (R_i) corresponding to the defective grates. The result of the particle filter is shown in **Figure 10**.

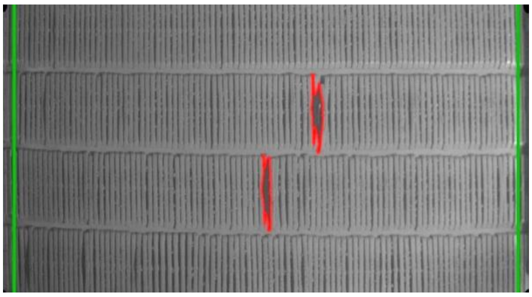

Figure 10: Defect detection result using particle filter based on width

To quantify the defect regions, we can compute the defect area % using **Equation 17**.

$$Defect\ area\ \% = \frac{\sum Area(R_{defective})}{\sum Area(R_{ideal})} \times 100\#(17)$$

Where $R_{defective} \in R_i \forall W_i \geq T$ and$\sum Area(R_{ideal})$is obtained from a car image which does not have any defects in it i.e. an ideal car. Defect area % can be used to classify the defective regions based on the stage classification described in section 1. Using the above described image processing algorithm, we have been able to achieve ~99% of defect detection in grate bars.

4. Embossed number recognition

Embossing numbers on industrial products is one way to store information about it for identifying and retrieving it at a later point in time. Metal embossed characters are widely used in industry because they are hard to alter and permanently preserved. A high-speed character recognition system for industrial products is very desirable to aid quality assurance and tracking of it. Traditional method of using a human to read the numbers are unsuitable for today's pace. Automated vision systems are the best alternative for such repetitive tasks to improve accuracy and productivity. Optical character recognition (OCR) techniques such as license plate recognition, document recognition and image to text converters have been developed over the years successfully [9] - [12]. However most of them work flawlessly for images with high print quality and often fail to produce optimal results when applied to embossed numbers. This happens due to low contrast between the foreground and background of embossed characters as both are very similar in color [10]. Further, over a period, oxidation or rust on the metal surface reduces the contrast between the characters and the background. Such numbers are hard to read even for a trained human [11].

OCR algorithms consist of two parts viz, character segmentation and character recognition. Several researches on text recognition under different scenarios such as printed document exists, however OCR for embossed number for industrial applications is limited and are constrained by the overall print features such as color, font and object view from camera [12].This section describes the basic image processing and mathematical preliminaries followed by building the algorithm to recognize embossed number in a car.

4.1 Mathematical preliminaries

Correlation in image processing is an operation which works by scanning through the image and applying a kernel to each pixel. The kernel coefficients weight the pixel intensity values they are overlapping with and correlation is computed as the sum of the weighted pixel intensity values. Concretely, we correlate the input image $f(x,y)$ with the kernel $h(x,y)$ and the result is $g(x,y)$. Mathematically it is expressed as **Equation 18 and 19**.

$$g(x,y) = f(x,y) \cdot h(x,y) \#(18)$$

$$g(x,y) = \sum_{j=-s}^{s} \sum_{i=-s}^{s} h(i,j) \cdot f(x+i, y+j) \#(19)$$

Where s is the radius of the kernel. Below is a pseudo-code to implement correlation between two images is shown.

```
for(y = s; y < (M - s); y = y + 1)
{    for(x = s; x < (N - s); x = x + 1)
     {    temp = 0
for(j = -s; j < (s + 1); j = j + 1)
         {    for(I = -s; i < (s + 1); i = i + 1)
              {    temp = temp + h(i ,j) * GetPixelValue(input, x+ i, y+j) }
         }
         SetPixelValue(output,x,y,temp)
     }
}
```

Where M and N are the row and column length of the input image.

In image processing, correlation measures the amount of similarity between two images of unequal sizes. By scanning the first image(template) over the second image(target), the correlation between them is computed. One of the important application of correlation is template matching. Template matching is used to locate a similar image in another image. When we apply template matching, the kernel becomes the template image. The template is defined as the image of an object we are searching for in another image. We now correlate the template with an image to find its presence in it. Each pixel in the output image has a value which denotes the similarity between the template and the image at that pixel location. The higher the correlation value, higher is the similarity.

Normalized cross correlation is an updated version of the correlation approach that has been improved for the following reason:

A. The result of normalized cross correlation is invariant to the global brightness changes and the image intensity variations have less effect on this metric compared to the correlation method.
B. The correlation value obtained for a given image is normalized to [-1, +1] interval, where the normalized cross correlation value between two similar images tends towards +1 and for dissimilar image tends to -1.

Normalized cross correlation is used as a better alternative to measure the similarity between images for template matching problems. However, the method is susceptible to rotation and scale changes. Mathematically the normalized cross correlation(NCC) is given by **Equation 20**.

$$NCC = \frac{\sum_{x,y}\left[f(x,y)-\bar{f}_{u,v}\right]\left[t(x-u,y-v)-\bar{t}\right]}{\left\{\sum_{x,y}\left[f(x,y)-\bar{f}_{u,v}\right]^2\sum_{x,y}\left[t(x-u,y-v)-\bar{t}\right]^2\right\}^{0.5}} \#(20)$$

where (x) is the original image, $\bar{f}$ is the mean of image intensity in the region under the template, t is the template and $\bar{t}$is the image intensity in the template and (x, y) and (u, v) are pixel coordinates.

4.2 Algorithm and result

Each car has a unique number embossed on it which helps to track its position in the induration conveyor.The recognition of this number is crucial to display the position of the defective car in the conveyor using our machine vision system. There are several well established Optical Character Recognition(OCR) algorithms present which can perform the task of reading text from images. These provide excellent results when the image contains printed text or characters having standard fonts and a contrast between the background and foreground. However, they mostly fail to recognize embossed number since the contrast between foreground and background is very low. Embossing is frequently adopted on metallic surface to make the characters resistant to damage. In general, it is a challenge to detect embossed number on metals.

We have employed an approach to recognize the number using a directional lighting setup. When an embossed character is illuminated by directional lighting, it casts a shadow corresponding to the shape of the character. **Figure 11**shows the comparison in the contrast between the foreground and background for front light vs directional light. It is evident that the directional light technique is producing the shadows corresponding to the shape of the characters and enhancing the contrast between the characters and the metallic background.

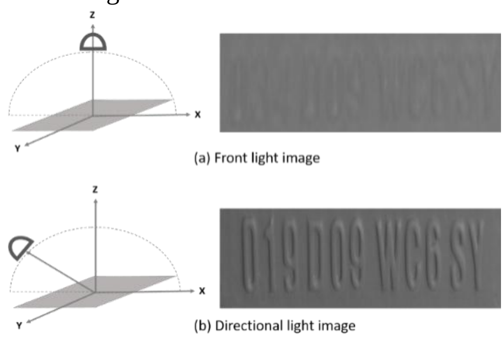

Figure 11: Comparison of image using front light vs directional light

In our method, we process the image captured by second camera which captures the car number. Like grate bar image, there is a tilt in the car number due to skew between the plane of image sensor and the plane of object. We apply the technique used previously to correct for the deformity using a transformation matrix obtain by 4-point perspective transformation using Equation (1). **Figure 12** shows the result of this perspective transformation on the actual image.

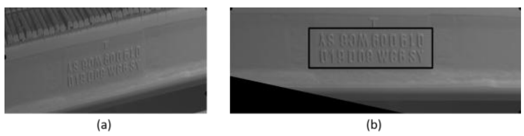

Figure 12: Transformation matrix result (a) Original image (b) Perspective corrected image

We perform a local adaptive thresholding to enhance the regions of the shadows and suppress the remaining background. This step acts as a filtering procedure in which the uniform background is concealed and the regions near the shadow of the characters are amplified. **Figure 13**shows the resultant image after adaptive thresholding. We call this image as the feature image $f(x, y)$.

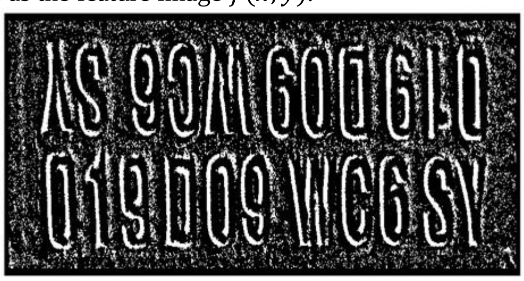

Figure 13: Enhance the shadow regions in the image

The numbers of all cars are known a priori as there are only a finite quantity of cars running in the conveyor and few more are kept in reserve for replacement and repair. A unique feature image is computed for all cars and stored in a database. Also, to improve the accuracy of the recognition algorithm, multiple feature images are computed for the same car to compensate for any minor change in illumination conditions. This database serves as the master templates for all the car numbers. We denote this as $s(x,y)$. A lookup table is also created which stores the actual car number corresponding to each image in $s(x,y)$.When the conveyor is running, a new feature image $f^{'}(x,y)$ is obtained for the current car. A template matching algorithm is used to search through $s(x,y)$ using $f^{'}(x,y)$ as the target. It computes a normalized cross correlation between the target image and all the images stored in $s(x,y)$ and provide a score R corresponding to each comparison. The image $s_i(x,y)$ corresponding to highest score of R is looked up in the table to obtain the actual car number.

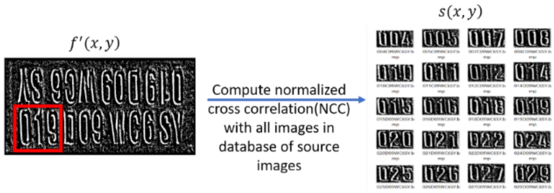

Figure 14: Using template matching to compare between target image and database images

Figure 14represents the process of comparison between the target feature image and the database of all feature images to obtain the car number corresponding to the highest score of the template matching.Incorporating the above approach of recognizing the embossed characters on the car we have been able to achieve an accuracy of ~92%. The false detections are caused by sporadic changes in illumination which disturbs the grayscale distribution of the captured image and causes mismatch in template matching.

5. Benefits

Pellets are raw material for blast furnace and shortage or inferior quality of it adversely impacts the volume and grade of iron making. In FY 2019-20, the pellet plant in Tata Steel, Jamshedpur recorded a delay of 434 minutes in plant operation due to replacement of undetected defective grate barsduring production.**Figure 15** shows the monthly distribution of delay caused by grate bar defects.

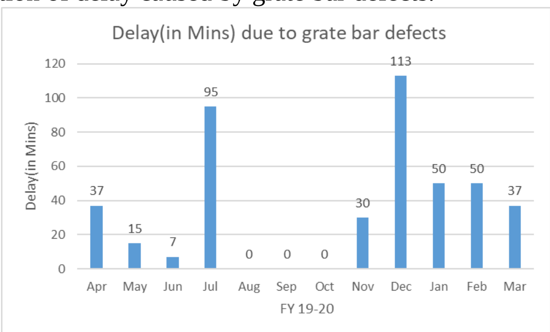

Figure 15: Delay in Mins due to grate bar defects in Pellet plant

Undetected defects in the induration conveyor resulted in pellet production loss amounting to over 5000 Tons due to unplanned breakdown within the same period.**Figure 16** shows the comparison of pellet production loss before and after the installation of our machine vision system at pellet plant.

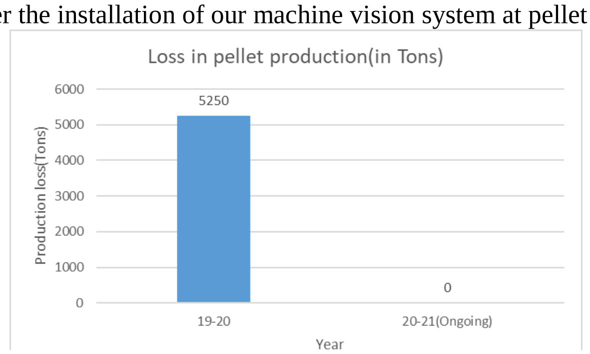

Figure 16: Pellet production loss

Our machine vision system eliminates the production loss by leveraging on custom image processing algorithms described in this paper to detect, track and notify the imminent state of conveyor defects. A graphical user interface updates the car status on a virtual conveyor for constant monitoring and notification for operator. This improvement in the efficiency and production capability of pellet plant will ensure uninterrupted supply of pellets to blast furnace for iron making and directly impact the revenue generated by the company.

6. Conclusion

The defects occurring in the induration conveyor of pellet plants adversely affect the critical process parameters of palletization of iron ore fines and impacts the quality of hot metal produced in the blast furnace. This paper showcases an image processing based method to find the defects in the conveyor using an adaptive thresholding and width based particle filter approach. Our approach can detect 99% of the defects occurring in the car using a machine vision system employing custom image processing algorithms. Also, we have presented a method to recognize the embossed car number using a template matching based image processing algorithm which enables us to track and locate the defective car in the conveyor. We have been able to achieve a high accuracy of 92% in recognizing the embossed characters using multiple template for each car in our database for comparison. For further improvements, we can explore feature based template matching to increase the accuracy of the number recognition and handle sporadic illumination changes in the vision system.

7. References

[1] Moraes, Sandra & Lima, José & Ribeiro, Tiago. (2018). Iron Ore Pelletizing Process: An Overview. 10.5772/intechopen.73164.

[2] Ball D. Agglomeration of Iron Ores. New York: American Elsevier Pub. Co.; 1973

[3] Metso. Iron ore pelletizing [Internet]. 2017. Availablefrom: http://www.metso.com/products/iron-ore-pelletizing/

[4] Sang uk lee, seokyoonchung and Rae hong park, “A Comparative Performance Study of SeveralGlobal Thresholding Techniques for Segmentation”, Computer Vision Graphics And Image Processing52, 171-190, 1990

[5] N. Otsu. A threshold selection methodfrom gray level histograms. IEEE Trans.systems. Man. and Cybernetics, 9:62–66,1979.

[6] Rukhsar Firdousi, Shaheen Parveen,” Local Thresholding Techniques in Image Binarization”,International Journal Of Engineering And Computer Science ISSN:2319-7242 Volume 3 Issue 3March, 2014 Page No. 4062-4065.

[7] Niblack (1986), An Introduction to Digital Image Processing, pp. 115 - 116, Prentice Hall.

[8] J. Sauvola and M. Pietikainen, “Adaptive document image binarization,” Pattern Recognition 33(2),pp. 225–236, 2000.

[9] K. Elagouni, C. Garcia, Text recognition in multimedia documents: a study of two neural-based OCRs using and avoiding character segmentation. Int. J. Doc. Anal. Recognit. 17(1), 19–31 (2014)

[10] R.F. Moghaddam, C.M. AdOtsu, An adaptive and parameterless generalization of Otsu’s method for document image binarization. Pattern Recogn. 45(6), 2419–2431 (2012)

[11] H. Caner, H.S. Gecim, A.Z. Alkar, Efficient embedded neural network based license plate recognition system. IEEE Trans. Veh. Technol. 57(5), 2675–2683 (2008)

[12] R. Panahi, I. Gholampour, Accurate detection and recognition of dirty vehicle plate numbers for high-speed applications. IEEE Trans. Intell. Transp. Syst. 18(4), 767–779 (2017)

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