ABSTRACT: With a variety of image processing and pattern recognition methods, the image characteristics of both stone and lump coal have been studied in this paper. It is found that the texture characteristics are most significant as far as separation is concerned. A separation algorithm based on Mahalanobis' distance discrimination function is also developed. The corresponding method has been tested in the lab with large samples of lump coal and stone on a moving belt. The results are quite encouraging.

1. INTRODUCTION

With the development of pattern recognition and digital image processing technology in the past two decades, various computer vision systems have been widely used in many industrial fields. The computer vision system not only has the outstanding advantage of high efficiency, but also provides a revolutionary novel means for solving many old industrial problems. The cost of such a system has been constantly declining over the past decade. Therefore, the potential of its application is still great.

In the coal industry, there are three traditional methods for separation of stone from lump coal (size>=80mm) which have been widely used over the past hundred years. They are manual separation, heavy-medium cyclone, and smashing then jigging. There are many problems with all these traditional processes, especially considering environmental protection, operation cost and operation efficiency. The computer vision system here is developed to separate stone from lump coal on moving belts with the help of robots. This system may provide a possible revolutionary alternative for coal preparation processes.

2. System Construction

The hardware structure of the vision system is outlined in Fig 1. An industrial TV camera, RCA-170, and a PC-VISION frame grabber plugged into an IBM-PC/XT computer are used as image sampling devices. A powerful Sun 3-160 workstation is used for image processing. The IBM-PC/XT and Sun 3-160 are Ethernetted. The sampling rate of the PC-VISION frame grabber is thirty frames per second with the resolution of 256*256*8 bit each image frame.

The major functions of the system are image input, pre-processing, characteristics extraction, pattern recognition and results output.

3. Extraction of Characteristics

According to the perceptual knowledge of workers at the manual separation process-line in coal preparation plants, there likely is some lustre on the surface of lump coal under good lighting conditions, and stone usually looks murky gray. Therefore, it is quite possible for a computer vision system to discriminate stone and lump coal on moving belts. However, both stone and lump coal appear to be the same as far as human eyes can tell, even though, we have worked for the coal...
mining industry for over a decade. After
exclusive study of some characteristics
of both stone and lump coal, their
texture characteristics appear to be the
most significant. The major steps of
extracting image texture characteristics
include the following steps:

1. First, it is necessary to
separate the objects from their
background using threshold-gray level
method as follows:

\[ F(x, y) = \begin{cases} f(x, y), & \text{when } (x, y) \in T_1 \\ 0, & \text{when } (x, y) \in T_2 \end{cases} \]  

(1)

where \( f(x, y) \) is the 256*256 input image
gray level matrix, \( F(x, y) \) is the output
matrix, and \((x, y)\) is the pixel
coordinate. \( T_1 \) and \( T_2 \) stand for an object
(either stone or lump coal) and
background, respectively. \( T_1 \cap T_2 = \emptyset \). Since
stone, lump coal and belt are all black,
the separation was difficult. A method
based on both vertical and horizontal
scanning after boundary enhancement was
developed and appears to be quite
successful.

2. If the input image is quite
noisy, it should be filtered using the
following algorithm:

\[ F(x, y) = \begin{cases} 0, & \text{when } (x-k, y-l) \in T_3 \\ \sum f(x-k, y-l) * H_1(k, l), & \text{otherwise} \end{cases} \]  

where \( H_1 = \begin{bmatrix} 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \)

(2)

3. A differentiated gray level
matrix is then calculated as:

\[ Y(x, y) = \begin{cases} 0, & \text{when } (x-k, y-l) \in T_4 \\ \sum f(x-k, y-l) * H_2(k, l), & \text{otherwise} \end{cases} \]  

where \( H_2 = \begin{bmatrix} -1 & -1 & 1 \\ -1 & -1 & 1 \end{bmatrix} \)

(3)

4. The coefficient of bright point
will be:

\[ \eta = \frac{N_1}{M} \]  

(4)

where \( N_1 \) stands for the number of bright
points that satisfies \( Y(x, y) > T \) and \( T \) is
a third value of differentiated gray
level. \( M \) stands for the number of total
pixels of the object.

5. In order to obtain a
co-occurrence matrix of gray level and
differentiated gray level, it is
necessary to unify the gray level matrix
\( F(x, y) \) and the differentiated gray level
matrix \( Y(x, y) \).

\[ F'(x, y) = \text{INT}[F(x, y) * \frac{F_{\text{max}}}{F_{\text{max}}} + 1] \]  

(5)

\[ Y'(x, y) = \text{INT}[Y(x, y) * \frac{Y_{\text{max}}}{Y_{\text{max}}} + 1] \]  

where \( F_{\text{max}}, Y_{\text{max}} \) is chosen

(6)

6. \( Q(m, n) \), the gray level and
differentiated gray level matrix, is
defined as the number of pixels that
satisfy \( F'(x, y) = m \) and \( Y'(x, y) = n \). In other
words, the element value of \( Q(m, n) \) is the
total number of pixels where the unified
gray level is \( m \) and the unified
differentiated gray level is \( n \).
Therefore, \( Q(x, y) \) is very informative.

7. Suppose the probability
distribution of \( Q(m, n) \) is:

\[ P(m, n) = \frac{Q(m, n)}{N} \]  

(7)

then the following characteristics of the
image may be extracted:

a. big difference dominance

\[ Bd = \frac{\sum_{m,n} n \cdot Q(m, n)}{\sum_{m,n} Q(m, n)} \]  

(8)

b. mean of gray value

\[ \mu_1 = \frac{1}{M} \sum_{m,n} P(m, n) \]  

(9)

c. mean of differentiated gray level

\[ \mu_2 = \frac{1}{M} \sum_{m,n} P(m, n) \]  

(10)

d. standard deviation of
differentiated gray level
(8) let \( x_1=100n, x_2=0.01Bd, x_3=1.0 \), then characteristics vector \( x = \{x_1, x_2, x_3, x_4, x_5\} \) is finally obtained.

4. PATTERN RECOGNITION

In order to separate stone from lump coal, some pattern recognition technique has to be implemented. Several methods have been tried: a) Bayes decision method which calculates the possibilities of an unknown sample belonging to coal and to stone, respectively, and classifies the sample to the group with higher possibility; b) linear discrimination polynomial which try to separate two groups by a simple plan in the characteristic space; and c) Mahalanobis distance method which appears to be the best choice and is described below.

The characteristics vector of the images concerned has \( d \)-dimension and only two possible types of images (coal and stone) are to be distinguished. Therefore, such \( d \)-dimensional pattern space could be imposed on the population of lump coal \( W_1 \) and stone \( W_2 \), respectively, and if \( x \in W_1 \), then \( x \in W_2 \). Population \( W_1 \) and \( W_2 \) have \( d \)-dimensional mean vector \( m_1 \), \( m_2 \) respectively, and \( d \times d \) nonsingular covariance matrix \( C_1 \), \( C_2 \), and the pattern space is a \( d \)-dimensional Euclidean space \( \mathbb{R}^d \), where total population is \( W=W_1+W_2 \). Mahalanobis distance between any two patterns \( x \) and \( y \) in \( \mathbb{R}^d \) is:

\[
D(x, y) = \sqrt{(x-y)^T C^{-1} (x-y)}
\]  

where \( C \) is the nonsingular covariance matrix of \( W \). Similarly, Mahalanobis distance between \( x \) and \( W_i \) \( (i=1, 2) \) is

\[
D(x, W_i) = \sqrt{(x-m_i)^T C_i^{-1} (x-m_i)}
\]  

If the following discrimination function is chosen:

\[
g(x) = 0.5 \{ (x-m_1)^T C_1^{-1} (x-m_1) + (x-m_2)^T C_2^{-1} (x-m_2) \} + u
\]  

then the corresponding criterion will be:

\[
\begin{align*}
\text{if } g(x) > 0, & \text{ then } x \in W_1 \\
\text{if } g(x) < 0, & \text{ then } x \in W_2
\end{align*}
\]  

Offset \( u \) in formula (14) is selected according to the importance of \( W_1 \) and \( W_2 \). When \( W_1 \) is as the same importance as \( W_2 \), \( u=0 \), then \( x \) belongs to the nearer population. Since the distribution of \( W_1 \) and \( W_2 \) in \( \mathbb{R}^d \) space are unknown so that the parameters \( m_1, m_2, C_1 \), and \( C_2 \) in formula (14) can only be estimated using a number of given samples. If there are \( n \) known samples of \( W_i \) \( (i=1, 2) \), and their characteristic vectors are \( x_1, x_2, \ldots, x_N \) respectively, \( N_i \) is the number of the samples, then:

\[
\begin{align*}
m_i &= \frac{1}{N_i} \sum_{j=1}^{N_i} x_j \\
C_i &= \frac{1}{N_i} \sum_{j=1}^{N_i} x_j^T x_j - m_i m_i^T
\end{align*}
\]  

Obviously, such estimation is asymptotically unbiased. The greater the number of known samples, the more accurate the estimation will be.

According to the above method with estimated parameters, a large sample of lump coal and stone are tested in the lab. The error of mistaken stone is less than seventeen percent. The error of mistaken lump coal is less than six percent. The overall correct discrimination is better than eighty-five percent.

5. CONCLUSION

A computer vision system that separates stone from lump coal was developed. The primary test of the system in the lab was quite successful. The correct discrimination between stone and lump coal is better than eighty-five percent. The computer vision approach might be able to provide a revolutionary alternative for coal preparation in the future with an environmental advantage as well as low operation cost and less investment for a new plant. However, there is still something to be done in order to make the system practically useful in coal preparation plants. The major obstacle is the computing speed which takes one minute on a SUN
workstation for each separation at the moment. There are several possible approaches for the problem: a) powerful transputer approach; b) new discrimination algorithm approach, such as fuzzy discrimination; c) neural network approach. As far as the authors can see, the neural network approach may be most promising since the neural networks are inherently massive parallel and have a learning capability which may be extremely important for system flexibility to cover all kinds of coal and stone.

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REFERENCES
